ESP IJAST
ESP International Journal of Advancements in Science & Technology
ISSN: 2583-9233 / Volume 4 Issue 1 March 2026 / Page No: 60-68
Paper Id: IJAST-V4I1P108 / Doi: 10.56472/25839233/IJAST-V4I1P108

Original Article

Coal Mine Worker Safety Gloves

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Received Date: 22 February 2026 Revised Date: 28 February 2026 Accepted Date: 06 March 2026

***Abstract**: Coal mining ranks among the most dangerous job, with workers operating in underground conditions replete with toxic gases, higher-than-average temperatures, heavy machinery and unstable working environments. Workers are routinely exposed to dangers such as methane leaks, carbon-monoxide poisoning, explosions and sudden building collapses. To keep miners safe, smart mines need to continuously track environmental factors and monitor worker health condition. This paper focuses on the design and implementation of Smart Coal Mine Worker Safety Gloves, which are a wearable safety device capable of providing real-time hazard detection as well as emergency communication. The glove, which features sensors that detect harmful gases like methane and carbon monoxide, temperature swings as well as erratic hand movements. Gained data is processed by microcontroller and if unsafe condition detected then the worker will be immediately warned using vibrations and buzzer notification. Plus, the glove includes a panic button that allows workers to trigger an immediate distress signal by means of wireless communication modules sent to a control room or supervisor. Made interaction for rugged underground conditions, HDT's Underground System is "Light-Weight. The project aims to enhance occupational safety and emergency response efficiency in coal mining industry across varioushows by adopting the concept of integrated solution mobile workforce management through sensor technology, embedded system and also wireless communication technology. Our proposed glove is an effective, cost-efficient, and user-friendly solution for monitoring work-related hazards that would help improve the industry safety standards in the mine.*

***Keywords**: Smart Safety Glove, Coal Mine Monitoring, Edge AI Processing, Reinforcement Learnin, Hazard Detection System.*

I. INTRODUCTION

Written: Coal mining (October 2023) Coal is an essential industry that supports power generation and multiple industrial processes. It is vital, though often considered one of the deadliest professions. Miners work in underground settings that expose them to toxic gases, extreme temperatures, uneven ventilation systems, heavy machinery and collapsing rock structures. Worker safety has also been perilously compromised by accidents, including gas explosions and suffocation caused by leaks of carbon monoxide as well as bodies trapped beneath collapsed roofs or machines. Although helmets, masks and protective gloves are commonly used for protection, many of the traditional safety systems rely on static monitoring units or manual inspections. These processes may not be able to perform continuous monitoring on every individual worker. In this scenario, delayed hazard detection or distress signal communication can lead to loss of lives. That's why the idea of wearable safety technology is gaining traction as a potential fix for these problems. PPT ON IoT Based Smart Coal Mine Worker Safety Gloves. Sensors are used to detect gas, monitor temperature and motion in the glove with a microcontroller and wireless communication system. The new system provides a practical cost-effective monitoring solution that can withstand the extreme conditions often present in mining environments and can comply with strict occupational safety standards with real-time data available. The smart glove system can also potentially act as a tracker of physiological parameters such as heart rate or abnormal hand movements, in parallel with environmental monitoring. Being able to monitor the physical state of the miners also comes in handy, as one of the possible reasons for accidents might be fatigue or stress, or even sudden health issues. This should allow for early warnings, preventing critical situations through the identification of irregular patterns. Another important feature of the project is its emergency alert system. Additionally, the glove may include a push-button or gesture-based alert system so that miners can quickly notify a control room if they are in distress. When accidents occur, this also lessens the time in giving a response for help and permits the rescue services to easily trace affected workers so that they may be assisted immediately. The health parameters can be transmitted instantly to a central monitoring station using wireless communication technologies (such as GSM, Wi-Fi or Bluetooth). Supervisors can then monitor Environmental readings & worker status to make smart decision and improve upon safety management. Data logging functionalities can also help analyze incidents and take action to prevent a similar incidents in the future. Finally, the Smart Coal Mine Worker Safety Gloves project will be a leap forward in introducing technology into one of the oldest and also highest risk profession ours — mining. Through embedded systems, sensor technology and IoT-based communication, the system provides a preventative full-fledged solution for protecting workers while reducing workplace risks.

II. LITERATURE SURVEY

There have been several IEEE papers published during the year 2022–2023, discussing different aspects of safety system in under ground coal mine. Several studies have focused on real-time environmental monitoring system that detect grievous gases such as methane and carbon monoxide using IoT-based sensor network [1], [2], [4], [6], [9]. They act as early alert systems to prevent suffocation and other explosion incidents. But most of these solutions rely, not on personal wearable devices allocated to individual workers, but rather on static monitoring stations.

Wearable technologies were investigated in terms of protection of workers, including smart helmets [9], safety jackets [16] and sensor-based wearable modules [20]. These types of devices pair motion sensors, gas detectors and alarm systems to help provide greater situational awareness on-site. In particular, hand-worn systems (glove based) have been explored for activity and wellness sensing [7], [14], [27]. Since gloves touch the working environment directly, these studies demonstrate that they are appropriate platforms for small-scale sensor embedding. It was recognized that however, the devices preventing coal mine accidents from happening would considerably reduce the mortality and injury rate of underground coal miners (Zhang et al.

Other new work shows how artificial intelligence and predictive analytics can be used to advance safety monitoring systems. ML and DL techniques have been used to solve the problems of anomaly detection, safety compliance monitoring and hazard prediction [11], [18], [21], [25] and [28]. Artificial Intelligence (AI) systems that can foresight potential hazards before they take place also increase safety. The smart glove PPE provided in integration with such a detection framework would be there to help users proactively overcome an accident instead of passively providing threshold biased alerts.

Other features that have been addressed in the literature are the energy efficiency and communication reliability. Various low power IoT architectures [8, 16], edge-to-cloud frameworks [17, 20] and ultra-reliable wireless communication (URC) protocols for the underground domain have been developed. Underground mines usually lack good connectivity that makes edge-based processing and efficient power management critical for prolonged wearable device functioning.

Furthermore, ergonomic aspects technology innovation and sensor optimization using e.g. sensor fusion and embedded systems has been documented in recent publications [5], [15], [22], [30]. Such works highlight an essential requirement for small, portable and strong wearable gadgets capable of enduring intense mining atmospheres. Detection accuracy can be enhanced through multi-sensor integration approaches by combining an array of environmental and physiological parameters into a shared monitoring system.

So, details of smart IoT-based technology wearable safety solutions for mining environment can find plentiful from literature in [1]–[30]. Existing systems approach helmet-based or simple sensor-shelf based but not much work is done to design a fully interleaved descriptive multi-sensor safety glove for coal mine laborers. Moreover, a research gap exists for integrating gas detection, motion sensing and physiological monitoring parameters as well as emergency alert system implementation in such a system which could be wearable on glove along with AI based analytics and energy efficient communication. Wearable safety equipment: we can fill this gap with our Coal Mine Worker Safety Glove, which achieves a complete intelligent wear smart wearable safety solution for the underground mining environment.

For science writers, an excellent style manual is [7].

III. FUTURE SCOPES AND IMPLEMENTATIONS

A. Architecture of Smart Coal Mine Worker Safety Glove

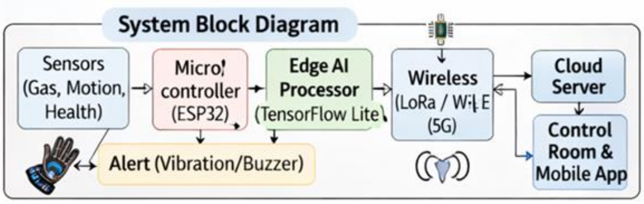

Figure 1 : System Block Diagram

Smart Coal Mine Worker Safety Glove Overall working architecture of It is as shown in the above system block diagram. The upper layer is the sensor layer — gas sensors (methane, carbon monoxide and so on), movement sensors (accelerometer/gyroscope), health sensors (heart rate, temperature) etc. They are continuously collecting real-time environmental and physiological data for both the worker and the mine environment. This raw data forms the underlying mechanism for hazard detection and safety monitoring.

The backbone of the glove is its microcontroller (ESP32) that receives input from collected sensor data. Some basic data processing happens at the microcontroller level; it sends important parameters to the Edge AI Processor (TensorFlow Lite). The Edge AI module leverages these trained ML/DL models to analyze the data for critical conditions including levels of gas that may exceed a danger level threshold, abnormal movements (such as falls), or other health condition indicators. An alert mechanism such as vibration motors or buzzers is activated immediately after a risky condition has been detected in order to notify the worker without exchanging any information from outside.

Simultaneously, routed data will be sent to cloud server from wireless communication module (LoRa, Wi-Fi or 5G). It stores data and performs complex analytics on a cloud platform and shares insights with the managers on their control room or mobile application. It enables remote monitoring, emergency response management and long-term safety evaluation. Hence, cloud system mobile/realtime alerts from local or edge processing of emergency detection providing holistic safety for coal mine labours.

B. AI & ML Architecture

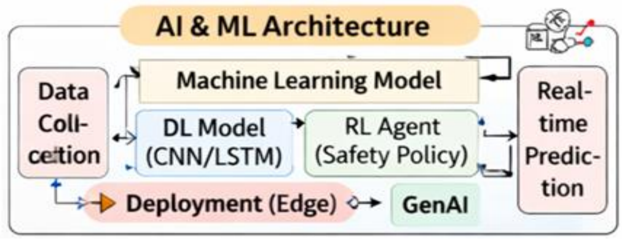

Figure 2 : AI & ML Architecture

The AI & ML Architecture used for the intelligent decision making of Smart Coal Mine Worker Safety Glove is shown in the second image of diagram. This process begins with data collection where sensor metrics such as gas composition, motion cues and health indicators are collected through the glove. This data is fed to the ML program which enables classification and prediction tasks (e.g., safe, warning, or danger). The ML-model involves training it with past mining safety data so that it can identify hazardous patterns accurately.

These could be the Deep Learning (DL) models in ML framework such as CNN(Convolutional Neural Network), LSTM(Long short-term memory) etc. that are capable of dealing with more complex data. CNN model is an analytical tool for extracting the presence of patterns from multi-sensor inputs and recognizing them, where LSTM networks analyze time-related processes such as heart rate trends or continuous gas background exposure levels [26]. In that regard, this RL agent acts as an optimizer of safety policy. The agent proactively learns and modifies the strategies for timely alert and responses to achieve an intelligent safety decision over-the-time (by responding in form of rewards or penalties) and adapt to diverse environments.

Once trained, the models are deployed at the edge (Deployment – Edge) using lightweight frameworks such as TensorFlow Lite for real-time processing. This enables quick hazard prediction with little reliance on the cloud. The GenAI module can extend this capability to produce everything from safety reports and risk summaries, cover tools used, voice/text alerts for workers and supervisors etc. The architecture ultimately produces real-time predictions that result in timely alert and proactive accident avoidance at an underground mining environment.

C. Smart Glove Hardware

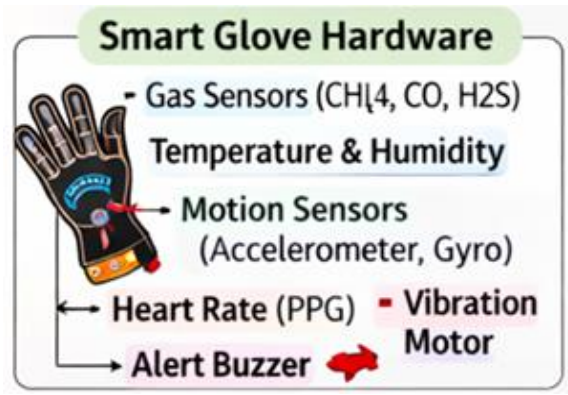

Figure 3 : Smart Glove Hardware

Smart Glove Hardware: This module incorporates the physical sensing and alert systems of a coal mine worker safety glove. The glove has gas sensors to detect toxic gases such as methane (CH_4), carbon monoxide (CO) and hydrogen sulfide (H_2S) usually produce underground due to coal mining. These sensors have the ability to continuously monitor air quality in the surrounding area around workers hand for hazardous gas leakage before arriving there. The climate conditions that can lead to heat stress with potentially unsafe working environments are evaluated through the help of temperature and humidity sensors.

It also includes motion sensors, such as an accelerometer and gyroscope, that can detect abnormal movements like a sudden fall or hand tremors, or long periods of inactivity. This is vital for detecting worker accidents or physical distress analysis in real time. » In addition to that, a special sensor in the glove (PPG – Photoplethysmography) is embedded to evaluate the workers' physiological condition. Monitoring vital signs also allows you to detect fatigue, stress or medical emergencies sooner rather than later which gives you a sense of security besides tracking environmental hazards.

It also features output alert components such as a vibration motor and buzzer for responding immediately. When potentially unsafe conditions are detected, a vibration motor gives immediate haptic feedback, allowing the worker to feel the alert even in noisy mining environments. You can choose to have a buzzer with it for audible warning. Therefore, relatively smaller dimensions, but provisioned with environmental sensing, motion tracking and physiological activity and real-time alert systems allow enough safety monitoring in the harsh mining environment.

D. Edge AI Processing

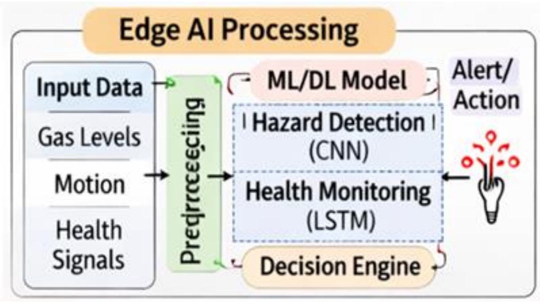

Figure 4 : Edge AI Processing

Smart Coal Mine Worker Safety Glove: Edge AI Processing module The edge processing core integrates the entire smart coal mine worker safety glove system where processing of all data occurs. The inputs data includes gas levels (CH_4, CO, H_2S), motion data (accelerometer and gyroscope) and health signals (heart rate, temperature). Depending on the raw sensor data being collected, a preprocessing step is required to filter out noise and extract relevant features. This will lead to feeding clean and structured data as input by the AI models for prediction.

This data is preprocessed and forwarded to the ML/DL models deployed at the edge. Multi-sensor environmental inputs (e.g., sudden gas spikes, abnormal motion events) are analyzed with a Convolutional Neural Network (CNN) for hazard detection via pattern recognition. Meanwhile, a Long Short-Term Memory (LSTM) network processes time-series health data to identify trends such as heart rate or long-term exposure to dangerous environmental conditions. These outputs are passed into a decision engine that weighs them against predefined triggers and learned behaviors to come up overall risk level (safe, warning or danger) whereupon it either makes a high or low risk/cross syntax call.

On risk confirmation, a real-time alert/action mechanism is executed by the system like vibration or buzzer sound and sending an notification. Since all this processing is done at the edge, literally at the glove itself that allows an instant response time and eliminates a total dependency on cloud connectivity. This low latency hazard detection based on edge computing will make the smart glove a very feasible option for deployment in underground coal mines, which may suffer from poor communication networks and lack of stability.

E. Cloud & GenAI Module

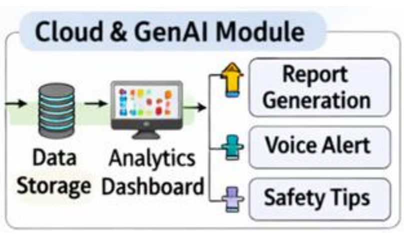

Figure 5 : Design for Cloud & GenAI Module

Cloud & GenAI Module (Centralized Intelligence and Analytics layer for smart coal mine worker safety glove) Sensor important data or risk alerts extrapolated after edge level processing is being sent over to the cloud server where such information is being stored securely in a structured database. This DB retains information for each unique historical records like gas levels, local motion patterns, individual health parameters and alert events. The long-term data storage may be used for purposes of trending, accident investigation and compliance reporting as required by mining authorities.

Using this data stored in the platform, an analytics dashboard processes that information into visual elements like graphs, heat maps and risk summaries. Supervisors and safety workers monitor the human condition in real time via control room systems or mobile applications. Going one step further than hazard zone pattern detections makes the ability to track worker behavior patterns available; assessing potentially and empirically deleterious behaviors, assisting with account performance reviews to put overall mine safety into a context relative both to people and processes. It is all monitored centrally, which allows for management to take steps proactively before accidents occur.

This smart part of GenAI processes the input data to create output instantly/automatically which in return requires little to no intervention. It is capable of writing detailed safety reports, summarizing risk events and generating predictive insights. Additional to this, GenAI can synthesize voice notifications or targeted safety orders for miner-specific situations that improve communication in emergencies. It could even offer context-sensitive safety tips, gently steering workers away from unsafe decisions. By infusing cloud analytics with generative AI capabilities, the system will provide not just reactive safety tools, but an intelligent safety management platform capable of evolution in coal mining operations.

F. Designs With Machine Learning Model

Figure 6 : Design for ML Models

Machine Learning Model The core framework that classifies safety conditions in the Smart Coal Mine Worker Safety Glove system is called the ML Model module, being a supervised learning model (Santos et al.

They begin with a sufficient dataset, i.e. data on gas levels in the mined and air flow that includes motion characteristics, modular parameters and health signals generated within mining environments. This dataset is divided into safe, warning and fatal cases. Processing the data also contributions in cleaning the training data with normalization, filtering noise, extraction of features etc which makes it meaningful for model development.

Supervised ML: Most supervised ML training phases use algorithms to identify patterns, such as Support Vector Machines (SVM), Random Forest K-Nearest Neighbors (KNN), or Gradient Boosting from labelled data. The relationships between sensor input and safety conditions are learned by the model as it minimizes the classification error 152. For example, a danger condition based on high methane concentration and abnormal motion. Once trained successfully, the model works as a hazard classifier to predict safety status when real-time data from glove sensors is fed into it.

Once deployed, ML model scores in real-time: Safe, Warning or Danger. If the system generates warning/ danger state, it will be triggered upon this prediction hence, response processing (vibration / buzzer) takes place. This classification-based approach enables the model to decide in very low time with low computational complexity, making it deployable on edge devices like ESP32 or lean AI processors. Therefore, the ML model is the bottom layer of intelligence in real-time WSH hazard detection for coal mine safety glove.

G. Designs With Deep Learning(DL)

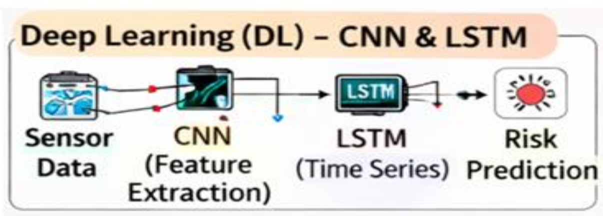

Figure 7 : Design for Deep Learning Model

You can see a brief description of individual modules below The Deep Learning (DL) – CNN & LSTM Module: The intelligent feature of Smart Coal Mine Worker Safety Glove: In this section- We have explained about Deep learning (DL), Which is a class of machine-learning algorithms that use many stages of representation and abstraction to model data. So they begin — as so many of these ideas do — with data from sensors: gas concentration; motion signals from accelerometers and gyroscopes; physiological signals like heart rate. Unlike traditional ML, which heavily relies on discovering high quality hand-crafted features, deep learning indicates strong search for advanced representation in raw or almost-raw sensing information.

The CNN is all about feature extraction. In particular, CNNs are performed well in extracting spatial features and correlations from either a single sensor or multiple sensors. An event like sudden vertical rise of methane levels or unusual pattern movements, to name a few, can actually be detected as potential hazardous events autonomously.

Feature extraction from sensor streams is done via a Convolutional Neural Network (CNN), which are then abstracted into one output that represents a semantically meaningful risk feature. Reducing the requirement of manual feature extractimproves the accuracy of detection in a complex subterranean environments.

The extracted features are fed into the Long Short-Term Memory (LSTM) network, which is a component of the model that focuses on the temporal data. LSTM models are a good fit for applications that express to learn progresses over time like development of toxic gas or suspicious motion heart rate. By utilizing its memory from previous states and understanding temporal inter-dependencies, an LSTM is able to predict risk level as a whole with greater accuracy.

The final output is the risk prediction (low, moderate and high danger) then routed to decision engine to trigger alert. These two excellent networks, CNN characterizing spatial information and LSTM layer representing temporal dependency channels, can build a solid GMF framework for coal mines real-time intelligent dangerous conditions recognition.

H. Design with Reinforcement Learning (RL)- Safety Policy

Figure 8 : Design for RL based Safety policy Model

Every goal could reduce redundancies, so the RL – Safety Policy module provides adaptive and intelligent decision to Smart Coal Mine Worker Safety Glove system. The environment in question is an underground coal mine and its details involve gas concentration variation, temperature changes, worker motion patterns and health states. The glove continually is checking this setting with its sensor and putting these readings in a state of the moment. This state is sent to the RL agent, which in this application setting is the Haslenet decision making component of the system.

The RL agent takes an action based on the observed state, the action can be either of making a vibration signal, sound buzzer alert to worker or send emergency notification, stop moving/ avoid hazard zone.

By using simulation to test out what happens as it interacts with the environment, reinforcement learning advances concept by concept instead of following a pre-defined set of rules. It uses some kind of reward mechanism to evaluate each action. In some examples, if an early warning averts exposure to a dangerous amount of gas or another threatened event occurs, the agent is rewarded positively.

If the alert is delayed, then higher risk and therefore a negative reward (penalty) will be given to the agent. “With repeated interactions, the RL agent is further trained to optimize its safety policy.

This type of dynamic learning can enable the glove to adjust when alerts are set off and at what level on-the-go. It learns from real operational data and adapts its reactions rather than responding on the fixed deterministic thresholds it starts with.

This RL-based safety policy is then learnt over time so as to deliver a faster, accurate and context-dependent reaction towards hazardous situations occurring in mining. Predicting accidents to make smart glove proactive & intelligent

IV. COMPARATIVE ANALYSIS OF THE TECHNOLOGIES

Table 1 : Comparison of Modern Technologies Used in Smart Coal Mine Worker Safety Glove

Technology	Purpose in System	Type of Learning	Processing Location	Advantages	Limitations	Suitability for Mining
Machine Learning (ML)	Hazard classification (Safe/Warning/Danger)	Supervised Learning	Edge / Cloud	Simple, fast, low computational cost	Limited in handling complex patterns	Good for basic real-time hazard detection
Deep Learning (CNN)	Feature extraction from multi-sensor data	Supervised Learning	Edge AI Processor	Automatic feature extraction, high accuracy	Requires more computational power	Excellent for gas + motion pattern detection
Deep Learning (LSTM)	Time-series health & gas trend analysis	Supervised Learning	Edge / Cloud	Captures temporal dependencies	Slightly higher latency than ML	Ideal for health monitoring & exposure tracking
Reinforcement Learning (RL)	Adaptive safety policy & alert optimization	Reward-based Learning	Edge / Hybrid	Self-learning, adaptive decision-making	Needs training time & reward tuning	Highly suitable for dynamic mine conditions
Generative AI (GenAI)	Report generation, voice alerts, safety tips	Generative Model	Cloud	Automated documentation, smart assistance	Requires strong cloud resources	Useful for supervision & safety management
Edge AI Processing	Real-time prediction without internet dependency	Deployed ML/DL Models	Edge (On-Device)	Low latency, works offline	Limited hardware resources	Critical for underground environments
Cloud Analytics	Long-term monitoring & visualization	Data-driven	Cloud	Scalable storage & analytics	Dependent on network	Suitable for control room monitoring
Wireless Communication (LoRa/5G/Wi-Fi)	Data transmission & alerts	N/A	Hybrid	Enables remote monitoring	Signal loss underground	LoRa best for underground mines

Safety assessment is lightweight and fast and thus highly relevant for the most restricted edge devices with minimal computational capabilities to act quickly in dangerous approaches, which makes ML a top candidate. Since you can automatically learn both spatial and temporal features from multi-sensor data jointly, Deep Learning (CNN and LSTM) excel in the advanced pattern recognition as well as continuous time-dependent health monitoring. This can be done by employing Reinforcement Learning (RL) into the system, which allows the safety glove to adapt itself when an alarm occurs, and progressively improve its decision-making process. Genai allows automatic report generation, voice alerts for real-time communication and safety suggestions contribute to the management of the safety in an organization. Underground mining cannot entirely rely on the availability of network connectivity, which means that low-latency (and preferably real-time) detection of hazardous events needs to be enabled—making Edge AI critical. Therefore, the cloud systems with communication technologies will be required for centralized supervision, persistent data analytics and remote monitoring to support integrated intelligence safety ecosystem.

Table 2 : Performance Based Comparison

Criteria	ML	DL (CNN/LSTM)	RL	GenAI
Real-Time Response	High	Medium–High	Medium	Low
Accuracy	Moderate	High	Adaptive (Improves over	Context-based

			time)	
Computational Requirement	Low	High	Medium	Very High
Power Consumption	Low	Medium	Medium	High (Cloud-based)
Adaptability	Low	Medium	Very High	Medium
Best Use Case	Basic classification	Complex hazard detection	Decision optimization	Reporting & assistance

From the comparison, it can be concluded that no one separate individual technology substitute can provide a safety net for coal mines. Machine learning offers fast classification, while deep learning provides improved accuracy; reinforcement learning allows for adaptive decision-making, and generative AI enhances reporting and communication. Edge AI guarantees processing in the locality (in real-time), while cloud systems support a centralized monitoring system.

So the use of ML, DL, RL and GenAI hybrid architecture leads to a holistic intelligent and robust Smart Coal Mine Worker Safety Glove system in future generation mining environments.

V. CONCLUSION

This paper presents a novel Smart Coal Mine Worker Safety Glove in which advanced technologies such as Machine Learning (ML), Deep Learning (DL), Reinforcement learning (RL), Generative AI, Edge Computing and Cloud Analytics were integrated to develop the glove. The work, in this rough paper gave guidelines on health; environmental safety for underground mining workers. Gas sensors, motion sensors, and health monitoring modules may be embedded in the smart glove to prevent the worker from being out of reach while still keeping them up on their feet. Therefore, with our Machine Learning, we can classify hazardous agent quickly and efficiently, and also identify multidimensional matching of disease concerning to environment and health using Deep Learning capability. Reinforcement Learning offers the ability to develop adaptive safety policies and optimizes on timing for alerts, thus minimizing nuisance alarms. Generative AI enhances the system by producing regular reports, voice alerts and safety suggestions for supervisors and employees. This of course is Edge AI processing, which supports low-latency decision making even in down connectivity environments like underground. Cloud integration provides centralized monitoring, long-term data storage and even advanced analytics. This hybrid model helps improve the safety system's reliability, scalability and intelligence. The glove proposed in this research facilitates the transition from classical (retrospective) safety to proactive or even predictive safety features. In conclusion this project as a whole demonstrates or encapsulates the potential of technological development in AI to significantly reduce the occurrence of accidents and lead to safer coal mining practices for workers within that operation.

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