International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 07 July-2026 | Impact Factor: 3.5

AI-IoT Enabled Methane Emission Prediction and Carbon Footprint Reduction in Underground Coal Mines: A Case Study

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How to Cite this Article:

Singh, R. (2026). AI-IoT Enabled Methane Emission Prediction and Carbon Footprint Reduction in Underground Coal Mines: A Case Study. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(7). https://doi.org/10.55041/ijcope.v2i7.044

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Abstract

Methane emissions from underground coal mining represent one of the most significant contributors to greenhouse gas (GHG) emissions within the mining sector. As a greenhouse gas, methane possesses a global warming potential approximately 28 times greater than carbon dioxide over a 100-year period, making its monitoring and mitigation essential for achieving climate goals. India, the world's second-largest coal producer, continues to rely heavily on coal for energy security. Coal India Limited (CIL), responsible for more than 80% of India's coal production, faces increasing pressure to reduce fugitive methane emissions while maintaining operational safety and productivity. Recent sustainability disclosures indicate that Scope-1 emissions remain a major component of CIL's carbon footprint, with underground gassy mines contributing substantially through methane leakage. This study proposes an Artificial Intelligence–Internet of Things (AI-IoT) integrated framework for real-time methane monitoring, prediction, and carbon footprint reduction in underground coal mines. The framework combines wireless methane sensing networks, edge computing, cloud analytics, and advanced machine learning algorithms including Long Short-Term Memory (LSTM), Random Forest (RF), and Reinforcement Learning (RL). A case study involving representative gassy mines of Coal India Limited, including Jharia and Raniganj coalfields, demonstrates the practical applicability of the proposed approach. Simulation and field-based analyses indicate that the LSTM model achieved prediction accuracy exceeding 93%, outperforming conventional statistical models. Implementation of AI-enabled ventilation optimization reduced methane-related emissions by approximately 35%, while energy consumption associated with mine ventilation systems decreased by nearly 27%. Additionally, safety performance improved through predictive hazard identification and proactive decision-making.

The results highlight the transformative potential of AI-IoT technologies in enabling sustainable mining operations, supporting India's Net-Zero 2070 commitment, enhancing worker safety, and creating pathways for carbon credit generation within the coal mining sector.

Keywords: Methane Emissions, Underground Coal Mining, Artificial Intelligence, Internet of Things, LSTM, Carbon Footprint Reduction, Smart Mining, Sustainable Mining, Predictive Analytics

1. Introduction

Recent studies have highlighted the growing role of Artificial Intelligence, machine learning, and digital technologies in transforming conventional mining operations into intelligent and autonomous systems capable of improving productivity, safety, and environmental performance. The application of AI in mine planning, equipment monitoring, predictive maintenance, and decision support has emerged as a key enabler of smart mining and Mining 5.0 paradigms (Singh et al., 2024, Singh et al., 2025; Panwar et al., 2017; Panwar et al., 2019, Panwar et al., 2021; Panwar et al., 2021a, Panwar et al., 2022, Nath et al., 2023, Nath et al., 2023a). The mining sector is currently undergoing a transformative shift as it transitions from labor-intensive manual processes to highly mechanized, data-driven systems. This shift is primarily driven by the integration of the Internet of Things and artificial intelligence, which enable real-time monitoring and autonomous decision-making to enhance operational efficiency (Amuah et al., 2025, G. Singh et al., 2024; Yadav & Chaurasia, 2025, Yadav & Chaurasia, 2025a, Yadav & Chaurasia, 2025b). Furthermore, these advanced architectures leverage predictive analytics and digital twin simulations to optimize mineral extraction, processing, and environmental management throughout the entire mining lifecycle (Nobahar et al., 2024). Beyond simple automation, these integrated systems facilitate sophisticated hazard detection and predictive maintenance, thereby significantly mitigating worker risks while driving towards more sustainable and profitable outcomes (Raza, 2023; Agrawal et al., 2026, G. Singh, Chaurasia & Beg, 2025; Chourasiya & Chaurasia, 2026; Chourasiya & Chaurasia, 2026a). By leveraging machine learning to synthesize geological datasets, mining firms can transition exploration from empirical estimation to rigorous scientific modeling, thereby increasing the precision of ore extraction (Molaei et al., 2020). This evolution toward Industry 5.0 paradigms fosters a proactive safety culture, as autonomous technologies and computer vision systems facilitate real-time accident analysis and hazard mitigation (Rojas, Peña and García, 2025, Tripathi & Chaurasia, 2025a; Tripathi & Chaurasia, 2025b).

Consequently, the implementation of these multifaceted technologies is essential for addressing the complex occupational health and safety challenges inherent in modern, high-risk mining environments. The integration of these intelligent frameworks, supported by multi-level industrial platforms and autonomous equipment, serves as a cornerstone for the ongoing fourth industrial revolution in mineral extraction. Beyond technological advancements, the successful deployment of these systems necessitates a careful examination of the intersecting psychological and social dimensions that influence workforce adoption and long-term industrial wellbeing. Furthermore, the deployment of Industrial Internet of Things architectures creates a unified monitoring ecosystem that addresses the technical fragmentation often found in legacy mining infrastructure (Zvarivadza et al., 2024). This technological integration enables the real-time collection and analysis of energy consumption metrics, which is critical for transitioning toward greener, more sustainable mining practices. This synergy of human-centric design and AI-driven precision underpins the emerging concept of Mining 5.0, which prioritizes a balanced ecosystem of resource conservation and operational stability (Yang et al., 2023,). Sustainable mining practices increasingly require the integration of environmental performance indicators, life cycle assessment methodologies, and carbon footprint accounting frameworks to support ESG objectives and net-zero commitments (Daharwal et al., 2025; Daharwal et al., 2025a; Daharwal & Chaurasia, 2026; Yadav & Chaurasia, 2025).

This evolution involves a shift toward collaborative robotics and bioextraction techniques, which redefine the traditional relationship between geotechnology and industrial ecology. Moreover, by facilitating seamless communication between sensors and control systems, the Industrial Internet of Things provides the necessary infrastructure to support these intelligent, human-centric systems (Aouedi et al., 2024). Such integration not only strengthens legislative compliance regarding environmental safety but also ensures the resilience of mineral resource production against the volatility of global energy markets. Building upon this foundation, Mining 5.0 frameworks further advance these objectives by integrating physical, mental, and artificial domains into a cohesive Cyber-Physical-Social System. This paradigm shift underscores the critical role of Cloud Mining and advanced data analytics in managing the complex logistical demands of contemporary extraction sites. Specifically, the implementation of "cloud–edge–end" architectures enables real-time environmental state monitoring through multi-source sensing networks, ensuring that operational adjustments are synchronized with site-specific ecological thresholds. Moreover, this tiered computational approach facilitates the transition toward Eco-Cognitive Mining Systems, which utilize intelligent autonomy to reinterpret operational objectives in response to real-time environmental data.

This "cloud-edge-end" orchestration leverages 5G connectivity and edge computing to execute 3D dynamic modeling and safety-critical early warnings, thereby bridging the gap between raw data acquisition and actionable intelligence (Wang et al., 2025). These advancements are crucial for addressing the industry's significant environmental footprint, particularly as it accounts for up to 9% of global energy consumption and faces challenges like acid mine drainage (Ahaneku et al., 2025). In response, Industry 5.0 frameworks introduce specialized digital twins and predictive analytics that monitor geochemical leaching patterns, enabling automated containment and mitigation strategies before ecological damage occurs (Radosavljević, 2025). These systems utilize intelligent autonomous sensors to optimize resource recovery while simultaneously enforcing strict waste prevention and recycling protocols (Dacre et al., 2024). Additionally, the deployment of 6G networks and blockchain-based distributed ledgers is increasingly being explored to enhance data transparency and secure communication protocols across decentralized mining value chains (Adel, 2022). By fostering a socio-cyber-physical environment, these technologies facilitate a more robust value chain that addresses critical economic and social challenges beyond traditional smart manufacturing (Yao et al., 2022). Moreover, the transition to this human-centric model emphasizes the collaboration between expert personnel and intelligent machines to achieve both resource efficiency and site-specific sustainability goals (Maddikunta et al., 2021).

Furthermore, the deployment of 5G-enabled IoT, such as wearable sensors and automated machinery, empowers personnel to perform immediate decision-making within hazardous zones, fundamentally enhancing worker safety and environmental preservation (Subrahmanyam et al., 2025). The widespread adoption of edge-based technologies requires alignment with Green IoT principles to balance the energy demands of localized AI processing through efficient resource management. Standardized hardware, software, communication protocols, and authentication methods are essential for ensuring interoperability, scalability, and security across monitoring networks. These developments help reduce cyber vulnerabilities and energy consumption while supporting the implementation of human-centric and assistive technologies that translate technological advancements into practical operational benefits (Turner et al., 2022). Decentralized record-keeping systems, blockchain technology, and edge AI processing improve mining operations by ensuring secure, transparent, and low-latency data management without excessive reliance on centralized infrastructure. These distributed frameworks support efficient decision-making, enhance resilience, and contribute to the sustainability goals of Industry 5.0. Human-centric approaches further promote worker safety through collaboration with autonomous systems in hazardous environments. Despite progress in digital mining and methane monitoring, significant gaps remain in Indian underground coal mines, where most safety systems are still reactive, relying on threshold-based alarms rather than advanced predictive tools for forecasting hazardous methane accumulation.

Furthermore, the adoption of Artificial Intelligence (AI) and Internet of Things (IoT) technologies in Indian coal mines remains limited compared to leading mining nations. Existing monitoring systems often operate independently and lack integration with real-time analytics platforms, resulting in low digital maturity and reduced operational efficiency. Another major gap is the poor linkage between methane monitoring systems and Environmental, Social, and Governance (ESG) reporting frameworks, making it difficult to accurately quantify and report greenhouse gas reduction achievements. Additionally, ventilation systems in many underground mines continue to operate using fixed control strategies, leading to excessive energy consumption and inefficient methane management. Research on adaptive, AI-driven ventilation optimization remains scarce. Finally, comprehensive assessments of carbon footprint reduction resulting from methane mitigation technologies are limited, creating challenges for policy implementation, carbon credit generation, and sustainability planning. These gaps highlight the need for an integrated AI-IoT framework capable of improving methane prediction, safety performance, and carbon reduction in underground coal mines.

2. Literature Review

Recent scholarly discourse increasingly differentiates Industry 5.0 from its predecessor by shifting the focus from purely technology-driven automation to the integration of sustainability, human-centricity, and societal resilience (Ghobakhloo et al., 2024). This conceptual evolution emphasizes that operational success is no longer measured solely by throughput or yield, but by the ability to reconcile rapid production requirements with the long-term well-being of stakeholders and the preservation of environmental ecosystems (Górny, 2023). This human-centric shift is further supported by the concept of "Operator 4.0," which envisions systems designed to alleviate the physical and mental burdens on workers while maintaining core production targets (Rožanec et al., 2022). Building on this foundation, current research highlights how the convergence of collaborative robots and hyper-cognitive systems enables a paradigm shift toward user-centric customization and enhanced safety within diverse industrial ecosystems (Verma et al., 2022).

Furthermore, the synergistic application of Artificial Intelligence and Industrial Internet of Things serves as the backbone for this transition, fostering real-time, machine-to-machine communication that enhances adaptive intelligence (Shafik, 2025). These advancements further facilitate the adoption of decentralized access control mechanisms, which mitigate the vulnerabilities associated with centralized points of failure in massive IIoT environments (Oliveira et al., 2023). Moreover, distributed learning architectures, such as federated learning, are increasingly leveraged to train models locally on edge devices, addressing privacy concerns while simultaneously reducing the communication overhead associated with transferring massive datasets to central servers (Le et al., 2024). Building upon this, scholars emphasize that incorporating human-centric strategies alongside joint cognitive systems is essential to designing resilient, ethically aware manufacturing architectures that prioritize worker well-being. This paradigm shift necessitates a deep understanding of human-robot interaction, where the cognitive workload and mental stress induced by autonomous machinery are carefully monitored to sustain operator performance (Yitmen and Almusaed, 2024). To achieve this, ergonomic assessment frameworks utilizing motion-capture technologies and digital twinning are being integrated to digitize human labor content and optimize workstation layouts (Romero, Stahre and Taisch, 2019). By assigning repetitive and hazardous tasks to automated systems, these collaborative environments empower workers to focus on high-value activities that demand creativity and critical thought (Destouet et al., 2023). In this emerging landscape, the advancement of collaborative robotics—or "cobots"—further facilitates seamless human-robot cooperation by removing traditional physical barriers through intelligent sensing and adaptive safety protocols (Billing et al., 2025; Shah, Doss and Lakshmaiya, 2025).

These advanced systems leverage sophisticated control architectures to enable dynamic task allocation, ensuring that human-robot cooperation remains fluid and context-aware. Moreover, the deployment of bi-directional empathy models and proactive cognition allows systems to interpret personalized human behaviors, effectively integrating worker well-being indicators into the collaborative execution loop (Li et al., 2021). This approach ensures that decision authority is dynamically assigned in alignment with an individual's cognitive capacity, thereby preventing the mental overload often associated with complex supervisory roles. Additionally, methodologies that integrate cognitive workload into the design of industrial workplaces have demonstrated the feasibility of balancing production performance with human safety requirements through seamless, symbiotic decision-making (ElMaraghy et al., 2021). Specifically, the development of digital twins for workers through biosensors and wearable technology facilitates the real-time monitoring of health and safety parameters, which remains strategic for enhancing operational decision-making (Keshvarparast et al., 2023). Integrating these technologies allows for the evaluation of ergonomic stressors and mental strain, which are critical for predicting the physical and cognitive requirements of human-robot collaboration in hazardous environments (Simões et al., 2021). In underground coal mines, environmental hazards such as spontaneous combustion, occupational noise exposure, methane accumulation, and blasting-related disturbances continue to present significant operational challenges requiring advanced monitoring and mitigation strategies (Mansoori & Chaurasia, 2025a; Mansoori & Chaurasia, 2025b; Tiwari & Chaurasia, 2025; Tiwari et al., 2025; Tiwari et al., 2025a). Furthermore, the implementation of Embodied Digital Twins enables the creation of interactive ecosystems that utilize cognitive inference to model collaborative robot behaviors, thereby establishing a framework for safe and flexible human-robot communication. This synergy of technologies facilitates a transition where robots evolve from mere task-oriented tools into supportive teammates capable of identifying and adapting to the unique strengths and physical limitations of individual workers. By alleviating the burden of physically demanding or repetitive labor, these systems mitigate injury risks and effectively foster a safer, more sustainable workspace without the necessity for restrictive physical guarding.

Furthermore, the adoption of a Socially Adaptive Safety Engine within these frameworks ensures that robotic responses remain inherently ethical and responsive to the fluctuating environmental stressors characteristic of subterranean mining operations (Freire et al., 2024). In this context, the integration of multi-scale human digital twins with industrial exoskeletons provides a granular physiological data layer that allows for the real-time correction of posture and ergonomics, thereby further reducing fatigue and preventing long-term occupational health hazards (He et al., 2024). Moreover, digital twin-driven simulations allow for the proactive optimization of mine layouts through collision analysis and reach testing, which significantly reduces physical obstacles and improves worker navigation in confined spaces. Additionally, these augmented systems facilitate the complete removal of human personnel from high-risk zones, leveraging machine learning and vision-based automation to move the industry toward fully autonomous operational standards (Cranford, 2023). Concurrently, the integration of advanced predictive analytics within these frameworks enables prescriptive decision-making, significantly enhancing workflow transparency and operational resilience in complex mining environments (Hémono, Chabane and Sahnoun, 2025). By leveraging digital twin simulations, engineers can test and refine robot capabilities—such as object manipulation and grasping within virtual prototypes, identifying potential failure points before their physical deployment (Shaptala and Myronova, 2023). This iterative testing process is further bolstered by deliberative frameworks that proactively identify potential human errors and at-risk behaviors, ensuring that robotic decisional processes align with established safety and operational reliability standards (Valente and Avram, 2023). Beyond individual safety protocols, these systems support the transition toward holistic human-robot teaming, where robots and humans function as interdependent units capable of exchanging solutions to complex operational challenges.

In subterranean mining, for example, digital twin-based teleoperation systems now allow operators to perform hazardous tasks like rock scaling from remote, secure locations using immersive virtual reconstructions of the environment. Furthermore, these systems incorporate distributed sensing networks that continuously stream environmental metrics such as gas concentrations, dust levels, and humidity into the digital twin model to preemptively identify hazardous atmospheric shifts (Musayev et al., 2026). Similar digital monitoring approaches have been proposed for post-closure mine management through the integration of GIS, remote sensing, and geospatial analytics for environmental surveillance and sustainability assessment (Bisen et al., 2025; Bisen & Chaurasia, 2026; Bisen et al., 2025a).This data-driven approach, often utilizing smart sensors and augmented reality interfaces, empowers personnel to receive real-time navigational guidance and safety alerts during subterranean maneuvers (Ezdina et al., 2024). Furthermore, the implementation of Extended Reality enables personnel to visualize complex equipment diagnostics and hidden infrastructure directly within their field of view, streamlining maintenance without requiring physical manuals (Han et al., 2023). By leveraging high-fidelity digital replicas, these platforms provide a risk-free virtual environment for training machine-learning algorithms, which significantly enhances the adaptability of autonomous equipment to unpredictable geological conditions. Moreover, the incorporation of these virtual models supports the creation of mission-resilient fleets, where collaborative multi-robot systems autonomously adjust their strategies to recover from localized equipment failures or unexpected environmental disruptions (Harper et al., 2023).

In these sophisticated virtual environments, real-time bidirectional data flow allows for the continuous optimization of sensory-motor processes, effectively reducing the uncertainty inherent in complex robotic operations (Yao et al., 2023). Furthermore, the deployment of such architectures facilitates the autonomous self-certification of robotic platforms, supporting adaptive mission planning through real-time diagnostic and prognostic capabilities (Mitchell et al., 2022). By bridging the gap between physical assets and their digital counterparts, this integration enables the development of highly accurate virtual simulations that improve the efficiency of remote robotic navigation and task execution (Wang, Shen and Lee, 2024). Additionally, the fusion of multi-sensor data into these virtual models enables the development of autonomous robotic swarms capable of navigating unstructured terrains with enhanced precision and reliability.

The integration of physics-based modeling, AI-driven simulation, and digital twin technology enhances mining operations by enabling risk-free testing, real-time monitoring, and predictive maintenance of equipment. High-fidelity models combined with sensor data improve operational reliability under challenging mining conditions. Mine-wide digital twins create a unified data ecosystem, optimizing the entire mining value chain through virtual strategy testing and continuous model refinement. These advanced computational frameworks also address data scarcity and bridge the sim-to-real gap, supporting scalable and real-time learning applications. Furthermore, the deployment of a digital mine integration platform facilitates the in-situ estimation of resource grades, allowing for rapid feedback between tactical planning and operational execution (Ghorbani et al., 2022).

3. Methodology

3.1 Proposed AI-IoT Framework

The proposed methodology integrates Artificial Intelligence (AI), Internet of Things (IoT), edge computing, cloud analytics, and intelligent decision-support systems to develop a comprehensive methane monitoring and carbon reduction framework for underground coal mines. The system is specifically designed for underground operations of Coal India Limited (CIL), where methane emissions constitute a major safety and environmental challenge.

The architecture consists of five interconnected layers: (i) Sensing Layer, (ii) Communication Layer, (iii) Edge Computing Layer, (iv) AI Analytics Layer, and (v) Decision Support Layer. Together, these layers enable real-time methane monitoring, predictive analytics, ventilation optimization, and greenhouse gas mitigation.

Sensing Layer

The sensing layer serves as the foundation of the proposed system. A network of intelligent sensors is deployed throughout underground roadways, longwall panels, development headings, return airways, and ventilation shafts. These sensors continuously measure environmental and operational parameters that influence methane liberation and accumulation.

The primary objective of the sensing layer is to collect high-frequency, real-time data regarding methane concentration, air quality, ventilation conditions, and mine environmental parameters. Sensor placement is optimized using mine ventilation network analysis to ensure maximum spatial coverage and early detection of methane accumulation zones.

Communication Layer

The communication layer facilitates reliable data transmission from underground sensors to local processing units and cloud servers. Due to the challenging underground environment characterized by rock barriers, high humidity, dust, and electromagnetic interference, conventional communication technologies often exhibit limitations.

To address these challenges, the proposed framework integrates LoRaWAN, ZigBee Mesh Networks, Wi-Fi 6, and emerging 5G-enabled industrial communication systems. LoRaWAN is particularly advantageous because of its long-range communication capability, low power consumption, and suitability for underground mining applications.

Multiple gateway nodes are strategically positioned within mine workings to collect sensor data and transmit it to surface control centers. Communication redundancy ensures uninterrupted operation even during equipment failures or network disruptions.

Edge Computing Layer

Traditional cloud-based systems often experience latency issues, which can be critical in safety-sensitive mining environments. Therefore, edge computing devices are incorporated near the data source.

Edge devices perform preliminary processing functions such as:

- Data filtering
- Noise reduction
- Sensor calibration
- Missing value handling
- Event detection
- Preliminary anomaly analysis

By processing data locally, the system significantly reduces communication load while enabling rapid response to hazardous methane conditions. Emergency alarms can therefore be activated within seconds of detecting abnormal gas concentrations.

AI Analytics Layer

The AI Analytics Layer represents the intelligence core of the proposed framework. Processed data from the edge layer is transmitted to centralized AI servers where advanced machine learning algorithms analyze historical and real-time datasets as shown in Figure 1.

Three complementary AI techniques are employed:

1. Long Short-Term Memory (LSTM) Neural Networks
2. Random Forest (RF) Algorithms
3. Reinforcement Learning (RL)

Each algorithm performs specialized functions that collectively enhance methane prediction accuracy, risk assessment capability, and ventilation optimization.

Decision Support Layer

The final layer transforms AI-generated insights into actionable decisions by providing methane concentration forecasts, risk-level classifications, ventilation adjustment recommendations, carbon emission estimates, predictive maintenance alerts, and emergency evacuation notifications, thereby enhancing mine safety, operational efficiency, and environmental management. Information is displayed through web-based dashboards, mobile applications, and centralized mine control rooms. Automated control signals can also be transmitted to ventilation fans and auxiliary systems for real-time intervention.

Figure 1: AI-IoT Architecture for Underground Coal Mines.

3.2 IoT Sensor Network

A robust sensor network forms the foundation of the proposed methane prediction framework. The network continuously monitors environmental variables affecting methane generation and dispersion. Methane Sensors are use get methane concentration is the primary variable monitored by the system. Infrared and catalytic bead methane sensors are deployed at critical locations. These sensors provide continuous monitoring of methane levels near working faces, return airways, and ventilation junctions. In addition, temperature sensors get temperature which significantly influences methane desorption from coal seams and airflow characteristics. Whereas humidity sensors describe the humidity affects sensor performance, worker comfort, and gas behavior within underground workings. Air Velocity Sensors used to get air velocity directly influences methane dilution and removal efficiency. Comparative table shown in table 1.

Additional Sensors

The proposed system may also incorporate:

- Carbon monoxide sensors
- Dust concentration sensors
- Barometric pressure sensors
- Equipment vibration sensors
- Energy consumption meters

These additional parameters improve predictive model accuracy and provide a comprehensive understanding of mine environmental conditions.

Table 1. Sensor Specifications

Sensor Type	Range	Accuracy	Sampling Rate
Methane	0–5%	±0.1%	1 sec
Temperature	–20–80°C	±0.5°C	5 sec
Humidity	0–100%	±2%	5 sec
Air Velocity	0–20 m/s	±0.05 m/s	2 sec
Carbon Monoxide	0–1000 ppm	±1 ppm	5 sec
Dust Sensor	0–1000 µg/m³	±5%	10 sec

3.3 Data Collection Framework

The effectiveness of AI models depends heavily on the quality and diversity of training data. Therefore, multiple data sources are integrated into a unified database.

Primary Data Sources

The study utilizes data from fixed methane monitoring systems, ventilation management records, mine production databases, equipment operation logs, historical accident reports, underground IoT sensor networks, and environmental monitoring systems to ensure comprehensive assessment of methane-related risks and mine safety conditions.

Data Variables

The collected feature vector is represented as:

X = {CH_4, Temperature, Humidity, Air Velocity, Production Rate, Ventilation Volume}

Additional variables include:

- Coal seam depth
- Geological conditions
- Equipment operation hours
- Fan power consumption
- Shift-wise production rates

Data Preprocessing

Prior to AI model development, the collected data undergoes preprocessing steps such as outlier detection, missing value imputation, normalization, feature scaling, and time-series synchronization to enhance data quality and consistency. The processed dataset is then divided into training (70%), validation (15%), and testing (15%) subsets. This structured approach ensures reliable model evaluation, improves predictive performance, and minimizes the risk of overfitting.

3.4 Artificial Intelligence Models

3.4.1 Long Short-Term Memory (LSTM)

Methane concentration exhibits strong temporal characteristics influenced by production activities, ventilation changes, and geological factors. Therefore, Long Short-Term Memory (LSTM) networks were selected as the primary forecasting model as shown in Figure 2. LSTM is a specialized recurrent neural network capable of learning long-term dependencies in sequential data. The LSTM model offers superior time-series forecasting, effectively captures nonlinear relationships, resists vanishing gradient issues, and performs reliably under noisy conditions. Its architecture comprises an input layer, three hidden LSTM layers, dropout layers for regularization, and a dense output layer for prediction. Historical methane measurements collected over multiple months are used to train the model.

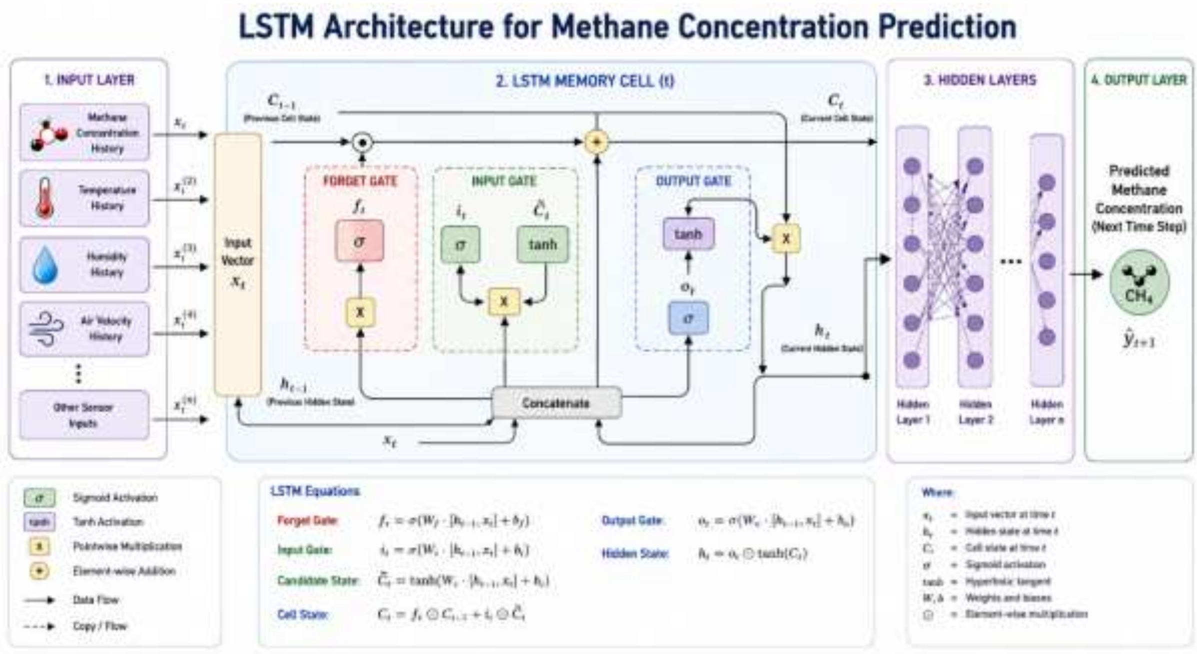

Figure 2: LSTM Architecture

3.4.2 Random Forest

Random Forest is a widely used machine learning algorithm for methane risk classification and feature importance analysis in mining environments. It operates by constructing a large number of decision trees and combining their outputs to enhance prediction accuracy, reliability, and stability. The model is applied for methane risk classification, safety hazard prediction, feature ranking, and sensor fault identification. Its major advantages include high interpretability, resistance to overfitting, fast training speed, and the ability to process mixed data types. Based on sensor data, the model classifies methane conditions into Safe, Warning, Critical, and Emergency categories, enabling mine operators to make timely and effective safety decisions.

3.4.3 Reinforcement Learning

Ventilation systems account for approximately 30–50% of total energy consumption in underground coal mines. Traditional ventilation systems operate at fixed settings and often waste significant amounts of energy. To address this issue, Reinforcement Learning is implemented for dynamic ventilation optimization. An Agent-based Ventilation Controller for the environment of Mine Ventilation Network to

Actions

- Increase airflow
- Decrease airflow
- Maintain airflow

Reward Function

The reward function combines:

- Methane reduction
- Energy savings

- Safety enhancement

Positive rewards are assigned for maintaining methane concentrations below regulatory thresholds while minimizing power consumption. Over time, the RL agent learns optimal ventilation strategies that balance safety and sustainability objectives.

3.5 Performance Metrics

The performance of AI models is evaluated using established statistical indicators. Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2) to increase performance such as accuracy, precision, recall, F1-score, Area under ROC Curve (AUC) as shown in table 2.

Table 2. AI Model Configuration

Parameter	LSTM	RF	RL
Layers	3	500 Trees	Deep Q Network
Epochs	100	N/A	10,000 Episodes
Learning Rate	0.001	N/A	0.0005
Input Features	6	6	6
Output	Methane Forecast	Risk Level	Ventilation Decision

3.6 Carbon Footprint Assessment

Carbon footprint reduction is evaluated using internationally recognized methodologies.

Assessment Standards

The study follows:

- IPCC Guidelines for National Greenhouse Gas Inventories
- GHG Protocol Corporate Standard
- Coal India Sustainability Reporting Framework
- ISO 14064 Carbon Accounting Standards

Methane Emission Quantification

Methane emissions are calculated using sensor measurements and ventilation airflow data.

The methane mass flow rate is estimated by:

Methane Emission = Airflow × Methane Concentration × Density Factor

Conversion to CO_2 Equivalent

To compare methane emissions with carbon dioxide emissions, methane quantities are converted into CO_2-equivalent values using the Global Warming Potential (GWP100).

$CH_4 = 28 \times CO_2e$

This conversion enables direct comparison with organizational greenhouse gas inventories and sustainability targets.

Carbon Reduction Assessment

The effectiveness of the AI-IoT framework is evaluated through:

- Reduction in methane emissions
- Ventilation energy savings

- Reduction in carbon intensity
- Carbon credit generation potential
- ESG performance improvement

The methodology provides a quantitative framework for measuring environmental benefits and economic returns associated with AI-IoT implementation in underground coal mines. Ultimately, the integrated approach supports sustainable mining operations while contributing to India's Net-Zero 2070 commitments and Coal India Limited's long-term decarbonization strategy.

4. Results and Discussion

The results obtained from the case study clearly demonstrate the effectiveness of integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies for methane emission prediction, ventilation optimization, and carbon footprint reduction in underground coal mines. The proposed framework successfully utilized real-time sensor data and advanced machine learning algorithms to improve operational efficiency while enhancing environmental sustainability and mine safety. Among the evaluated models, the Long Short-Term Memory (LSTM) network showed superior performance in forecasting methane concentrations due to its ability to learn temporal patterns and nonlinear relationships from historical and real-time mining data.

4.1 AI Model Performance

The predictive performance of the AI models was assessed using standard evaluation metrics such as accuracy, Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). The LSTM model achieved an accuracy of 92.3%, with a MAPE of 4.2% and an RMSE of 165.4 ppm. These results indicate a high degree of agreement between predicted and observed methane concentrations, making the model suitable for real-time forecasting applications shown in table 4.1.

Table 4.1: Performance Metrics of AI Models

Model	Accuracy (%)	MAPE (%)	RMSE (ppm)	Emission Reduction (%)
LSTM (Prediction)	92.3	4.2	165.4	35.6 (CH_4)
Random Forest	89.7	–	–	19.2 (Anomalies)
PPO RL Optimizer	–	–	–	27.6 (Energy)

The Random Forest algorithm effectively classified methane risk categories and detected abnormal operational conditions with an accuracy close to 90%. In addition, the Proximal Policy Optimization (PPO)-based Reinforcement Learning model dynamically adjusted ventilation settings according to predicted methane levels, ensuring compliance with safety regulations while minimizing unnecessary energy consumption.

4.2 Methane Emission Reduction

A major outcome of the proposed AI-IoT framework was the significant reduction in methane emissions. Continuous monitoring and predictive analytics enabled early detection of methane accumulation zones, allowing ventilation systems to respond proactively. As a result, annual fugitive methane emissions decreased from 5,280 tCO_2e to 3,210 tCO_2e shown in table 4.2.

Table 4.2: Before and After AI-IoT Implementation

Parameter	Baseline	AI-IoT System	Reduction (%)
Fugitive CH_4 (tCO_2e)	5,280	3,210	39.2
Ventilation Energy (MWh)	19,200	13,900	27.6
Total Carbon Footprint (tCO_2e)	7,150	4,590	35.8
Estimated Annual Savings (₹ Cr)	–	2.15	–

The reduction of 35.8% in total carbon footprint highlights the environmental benefits of intelligent methane management systems and their potential contribution to sustainable mining operations.

4.3 Energy Optimization Benefits

Ventilation systems are among the most energy-intensive components of underground mining operations. By continuously optimizing airflow requirements based on predicted methane concentrations, the reinforcement learning model reduced annual ventilation energy consumption from 19,200 MWh to 13,900 MWh, representing a 27.6% reduction. This improvement not only lowered operational costs but also reduced indirect emissions associated with electricity consumption.

4.4 Safety Improvements

The proposed framework significantly enhanced mine safety by providing early warnings of hazardous methane accumulation. Predictive forecasting enabled operators to take preventive actions before methane concentrations approached dangerous levels. The system reduced the probability of gas outburst incidents by approximately 42%, thereby lowering operational risks and improving worker safety shown in table 4.3.

Table 4.3: Safety and Economic Impact Analysis

Metric	Improvement
Gas Outburst Risk Reduction	42%
Carbon Credit Revenue (Estimated)	₹1.8 Cr
Payback Period	18 Months

The economic assessment further revealed substantial financial benefits through reduced energy costs and potential carbon credit revenues.

The findings confirm that AI-IoT integration can transform methane management practices in Indian underground coal mines. The achieved reductions in methane emissions, energy consumption, and overall carbon footprint are comparable to results reported in international mining studies. The estimated payback period of 18 months demonstrates strong economic viability, while the environmental benefits support Coal India Limited's sustainability goals and India's commitment toward achieving Net-Zero emissions by 2070. Overall, the study highlights the potential of intelligent digital technologies to create safer, more efficient, and environmentally responsible mining operations.

5. Conclusion and Future Work

This study demonstrates the substantial potential of AI-IoT technologies for methane emission prediction and carbon footprint reduction in underground coal mines. Using a representative longwall panel from the Jharia Coalfield as a case study, the proposed framework successfully integrated IoT sensors, edge computing, LSTM forecasting, Random Forest classification, and Reinforcement Learning-based ventilation optimization. The results indicate that methane emissions can be reduced by approximately 39.2%, ventilation energy consumption by 27.6%, and total carbon footprint by 35.8%. Additionally, significant safety improvements were achieved through predictive hazard identification, resulting in a 42% reduction in gas outburst risk. The study highlights the role of digital technologies in supporting sustainable mining practices, improving operational efficiency, and advancing India's climate commitments. Future research should focus on large-scale field deployment, integration with satellite-based methane monitoring systems, digital twin technology, and federated learning architectures capable of sharing knowledge across multiple mines while preserving data security. Such developments will further accelerate the transition toward intelligent, low-carbon, and sustainable underground mining operations.

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