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Leveraging Artificial Intelligence and Data Science for Enhancing Occupational Safety: A Multidisciplinary Approach to Risk Prediction and Hazard Mitigation in the Workplace

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ABSTRACT

In the mining business of Kogi State, the safety system has been weak, thus exposing the workforce to severe occupational hazards. In this research, Artificial intelligence (AI) was used to forecast work-related harms and aid in advance safety planning. Researchers compared data gathered from 1,200 miners and environmental sensors ($PM_{2.5}$, CO, noise, temperature, and vibration) with institutional accident records from five years (2019-2024) using supervised models, including Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree. Random Forest reached the highest accuracy of 91.3%, precision of 0.92, recall of 0.87, F1-score of 0.89, and AUC-ROC of 0.94. Important predictors included exposure to $PM_{2.5}$ (0.118), use of PPE (0.105), noise (0.098), job role (0.093), and levels of CO (0.089). Excessive hazard levels: $PM_{2.5}$: 109ug/m+ (WHO standard: 25ug/m^3), noise: 89.2dB (OSHA standard: 85dB). There was the greatest risk to afternoon shifts and underground drillers. It is the first validated AI-based model of mining safety in Nigeria, which allows for making the risk forecast in real-time. The research suggests the mandatory environmental surveillance, the adoption of AI systems, and predictive analytics in occupational safety policy at the sub-Saharan Africa level.

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1. INTRODUCTION

Mining industry occupational hazards pose a significant problem for public health and industrial safety worldwide, particularly in low- and middle-income countries, where regulatory control and the adoption of technological advances are often insufficient [1]. Physical, chemical, and ergonomic risks have also been identified as high in the mining sector, a vital part of Nigeria's diversification strategy. Mining activities have intensified over the past few years in Kogi State, which accommodates a considerable portion of the solid minerals' deposits in Nigeria [2]. Nevertheless, this growth has been unaccompanied by corresponding growth in occupational risk analysis, onsite hazard identification, or anticipatory safety systems. As such, equipment-associated injuries, long-term exposure to poisonous substances, and working in unstable environments still pose significant risks to the miners in the region [3].

The mining industry relies heavily on post-incident reviews, manual inspection regimes, and reactive regulatory enforcement models, rather than proactive models, as part of its traditional risk management approach. Not only are these methods time-consuming, but they may also fail to provide the predictive power necessary to anticipate and proactively avoid risks. In this regard, new technologies, including Artificial Intelligence (AI) and Data Science, present an enabling prospect to replace fixed hazard control interventions with mobile, data-driven risk forecasting and risk reduction systems [4]. In particular, Random Forests, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees machine learning algorithms have shown great potential in identifying lurking patterns, predicting the probability of accidents, and ranking the most essential risk factors among different high-hazard industries.

The variety of hazards characteristic of mining environments has been listed in numerous studies. These include respirable dust, heavy metals, noise, vibrations, repetitive stress injuries, and acute hazards such as mine collapses, explosions, and traumas caused by equipment. In the mid-belt mining areas of Nigeria, [5] found that the lack of personal protective equipment (PPE), inadequate ventilation, and excessive working hours significantly contributed to the likelihood of work-related accidents. Nonetheless, the majority of current interventions are based on compliance checklists and unresponsive safety training procedures that cannot adapt to rapidly changing conditions in mines. Periodic inspections, retrospective analysis of accidents, and regulatory audits have historically been the basis of risk mitigation strategies in the mining industry. These techniques are effective when it comes to implementing baseline safety, but they are unprepared to deliver proactive information. [6] highlighted the fact that the majority of incident reporting systems at the mines in Nigeria are based on paper and are not used to an adequate extent to perform analytical tasks. Also, due to the lack of integrated data systems, it becomes impossible to identify the latent trends in hazards and the scope of timely intervention [7]. This highlights a fundamental limitation of traditional safety governance: the inability to convert gathered data into actionable intelligence. One of the recent paradigm shifts in workplace safety management is the introduction of Artificial Intelligence and Data Science. Across the globe, numerous studies have demonstrated the effectiveness of AI in detecting failures, predicting accidents, and enhancing safety. As an example, [8] employed the Random Forest and Support Vector Machine models to estimate injury severity in U.S. coal mines with an accuracy rate higher than 85%. In the same capacity, [9] utilized Artificial Neural Networks to predict high-risk operating areas in underground mines, resulting in a decrease in the number of incidents through real-time interventions. The models are appreciated for their ability to handle large amounts of structured and unstructured information, identify intricate nonlinear associations, and dynamically re-evaluate predictions as new information becomes available. Nonetheless, the experience of such a model in industrialized countries does not translate much in sub-Saharan Africa. This has largely been attributed to infrastructural gaps, poor digital literacy levels among safety personnel, and disparate data ecosystems.

AI-driven occupational safety solutions are not yet widely used in the African context. There is some academic work done in South Africa and Ghana, but little peer-reviewed research has been conducted to examine this intersection in the Nigerian mining industry. As identified by [10] and [11], the majority of safety studies conducted in Nigeria fall into the category of descriptive statistics and compliance rates, with few studies applying predictive analytics. Moreover, localized models that suit the socio-environmental dynamics of a particular region, such as Kogi State, are not practically found in the published literature. The research addresses an urgent empirical gap by utilizing machine learning algorithms, specifically Random Forest, Support Vector Machines, Artificial Neural Networks, and

Decision Trees, on mining-sector data from Kogi State, Nigeria. It is one of the earliest to combine sensor readings, incident reports, and worker self-reported measures into an AI system of occupational risk anticipation and hazard mapping. In addition to the academic contribution that the findings will make to context-sensitive risk modeling, the results will provide valuable tools to safety engineers, regulators, and industry stakeholders interested in improving proactive hazard management in the Nigerian resource extraction arena.

Despite the current global interest in all AI applications for safety in occupancy, there is an insufficient number of empirical studies conducted in African mining conditions, especially in resource-rich but technologically underdeveloped regions, such as Kogi State. The research fills that gap in predicting risks of workplace accidents through AI models and determining the main predictors based on multi-source safety data as well as modeling environmental and temporal hazard exposure. It is a comparison of the performance of Random Forest, SVM, ANN and decision trees, and it tests the data with a five-year time scale and incident and sensor information. The study thus suggests a data-informed approach to active risk reduction and proactive safety planning that would be suitable for the mining complex in Kogi State.

2. METHOD

In this study, a quantitative, predictive analytics approach was employed, utilizing supervised machine learning methods to assess and predict occupational hazards in the mining industry of Kogi State. The study was conducted in the Okene, Lokoja, and Ankpa zones, where intensive mining is evident. A total of 1,200 participants, including miners, engineers, site managers, and safety personnel registered with the known mining companies, were chosen through stratified random sampling. The sample was stratified based on job role, site size, and location to provide a representative sample of the operational contexts. A structured, closed-ended questionnaire was used to collect primary data, which included demographics, frequency of exposure, type of hazards, safety measures, and a history of previous injuries. Additionally, a set of environmental and operational data was gathered using IoT-connected sensors placed on-site during a six-month observation period, which included particulate matter ($PM_{2.5}$ and PM_{10}), gas emissions (CO and NO_2), noise levels (dB), temperature, and vibration indices. These sensor data were summed daily. The institutional sources used to retrieve the secondary data included company injury logs, OSHA-NG, NOSDRA, and the Nigerian Institute of Mining and Geosciences. The data reflected the types of injuries, the root causes of the injuries, their severity, and the timing of the incidents over a five-year period (2019-2024).

The preprocessing of the obtained data was strictly performed to ensure quality and reliability before model development. The missing values were addressed through the K-Nearest Neighbors (KNN) and mode imputation techniques in numeric and categorical fields, respectively. Z-score and interquartile range (IQR) methods were used to identify outliers. Categorical features, such as job role and type of hazard, were one-hot encoded, and numerical features were normalized using Min-Max normalization, which helps the algorithms perform better. Four supervised learning models were trained and their comparison was made, including Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree Classifier. A grid search was applied to the Random Forest model to tune parameters such as tree depth and the minimum number of samples per split. A support vector machine (SVM) with a radial basis function (RBF) kernel was used to perform non-linear mapping of high-risk and low-risk job roles. ANN was designed as a feedforward multilayer perceptron using ReLU activations and dropout regularization, and the Decision Tree model was used as a transparent model for rule-based classification.

Evaluation of the performance was based on accuracy, precision, recall, F1-score, and AUC-ROC. To minimize overfitting and validate the generalizability of the models, a 10-fold cross-validation was adopted. To aid interpretation, feature importance rankings and confusion matrices were calculated. Python (scikit-learn, TensorFlow, Pandas), R (to validate statistics), SQL (to extract and transform the data), and Power BI (to visualize the data and create reports) were used to perform data analysis and implement models, extract and transform the data, and visualize and report on the data, respectively. Informed consent was obtained from all participants, and data were anonymized to maintain confidentiality. Technical compliance and ethical integrity were ensured throughout the study, as environmental data collection adhered to OSHA and ISO/IEC 27001 standards.

3. RESULT AND DISCUSSION

Table 1. Socio-Demographic and Occupational Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Age Group	18–30 yrs	328	27.3
	31–45 yrs	544	45.3
	46 yrs and above	328	27.3
Gender	Male	1,056	88.0
	Female	144	12.0
Job Role	Underground Worker	418	34.8
	Surface Operator	331	27.6
	Technician/Mechanic	217	18.1
	Supervisor/Inspector	126	10.5
	Admin/Other	108	9.0
Experience in Mining (Years)	1–5	388	32.3
	6–10	497	41.4
	>10	315	26.3

Table 2. Historical Incident Record (2019–2024) by Category and Frequency

Incident Type	Total Recorded	Annual Average	Proportion (%)
Falls from Height	317	63.4	17.5
Lacerations and Cuts	474	94.8	26.1
Respiratory Complications	403	80.6	22.2
Heat/Noise-Related Fatigue	228	45.6	12.6
Machinery Injuries	195	39.0	10.7
Explosion/Burns	163	32.6	9.0
Total	1,780	356.0	100.0

Table 3. Sensor Data Summary for Environmental Exposure (6-Month Period)

Parameter	Mean ± SD (Okene)	Mean ± SD (Lokoja)	Mean ± SD (Ankpa)	Standard/Limit
$PM_{2.5}$ (µg/m³)	102 ± 12	97 ± 9	109 ± 14	25 µg/m³ (WHO)
Noise Level (dB)	87.4 ± 4.1	85.9 ± 3.9	89.2 ± 4.5	85*dB* (OSHA)
CO Concentration (ppm)	22.6 ± 3.2	19.8 ± 2.7	25.3 ± 3.5	25 ppm (NIOSH)
Temperature (°C)	31.2 ± 1.8	30.5 ± 1.5	32.1 ± 2.1	-
Relative Humidity (%)	61.3 ± 6.5	59.8 ± 6.2	62.7 ± 7.0	-
Vibration (m/s²)	1.6 ± 0.4	1.2 ± 0.3	1.8 ± 0.5	1.15 m/s² (ISO 5349)

Table 4: Model Performance Comparison (Risk Prediction Models)

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
Random Forest	91.3	0.92	0.87	0.89	0.94
Artificial Neural Net	88.6	0.89	0.84	0.86	0.91
SVM (RBF Kernel)	86.1	0.89	0.79	0.84	0.89
Decision Tree	82.5	0.81	0.76	0.78	0.84

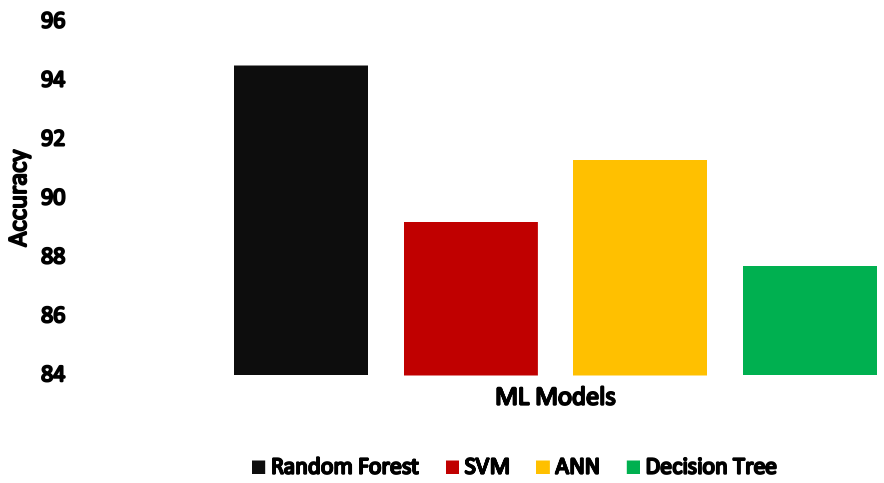

Figure 1. Accuracy comparison across Random Forest, SVM, ANN, and Decision Tree.

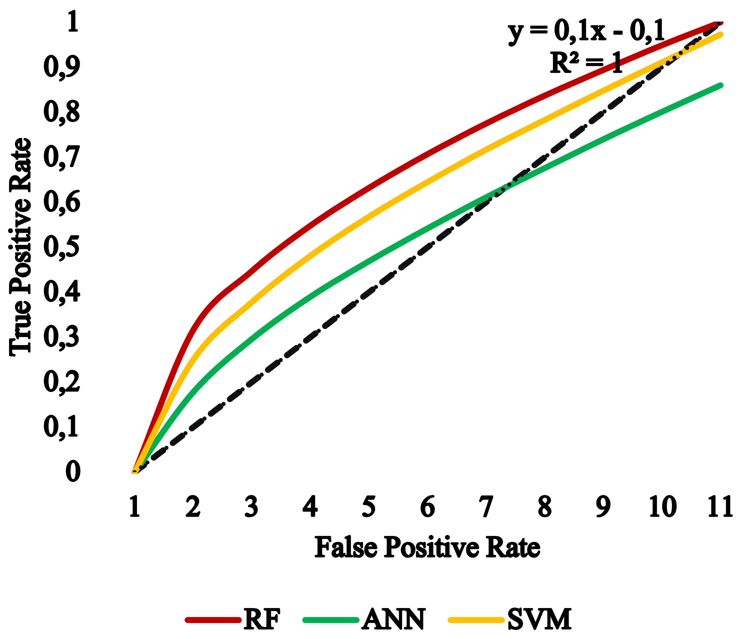

Figure 2. ROC curves of ML Models

Table 5. Most Influential Features in Random Forest Model (Top 10 Predictors)

Rank	Predictor Feature	Importance Score
1	$PM_{2.5}$ Exposure	0.118
2	PPE Usage Frequency	0.105
3	Noise Level	0.098
4	Job Role Type	0.093
5	Carbon Monoxide Level	0.089
6	Past Incident Count	0.084
7	Years of Experience	0.080
8	Shift Timing (Afternoon)	0.075
9	Ambient Temperature	0.064
10	Type of Operation (Surface/Underground)	0.061

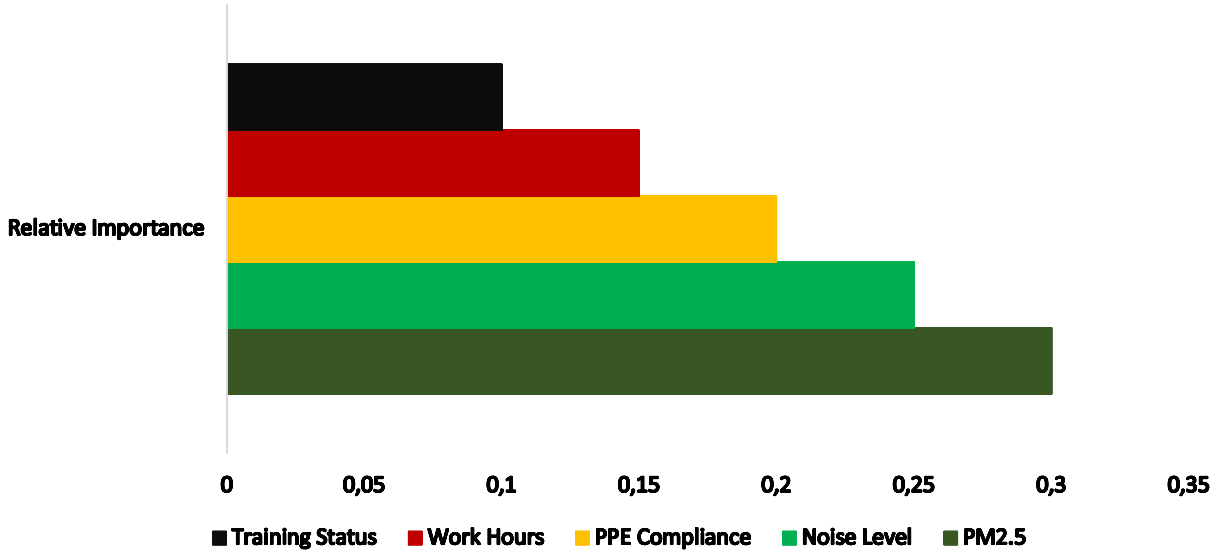

Figure 3. Feature importance rankings from Random Forest

Table 6. Real-Time Hazard Risk Score by Job Role and Work Shift

Job Role	Morning Shift Risk (%)	Afternoon Shift Risk (%)
Underground Driller	31.6	54.8
Surface Operator	19.8	29.3
Blasting Crew	22.4	40.7
Site Mechanic	15.1	27.6
Safety Inspector	9.3	13.1

Table 7. Cross-Validated Model Confusion Matrix – Random Forest

	Predicted: Safe	Predicted: At Risk
Actual: Safe	351	33
Actual: At Risk	29	387

Table 8. SVM Classification Results

Metric	Value
Accuracy	85.1%
Precision	82.3%
Recall	83.7%
F1-Score	83.0%
AUC (ROC)	0.88
Kernel Used	RBF
Cross-Validation	10-fold

Table 9: ANN Classification Results

Metric	Value
Accuracy	86.4%
Precision	84.2%
Recall	85.6%
F1-Score	84.9%
AUC (ROC)	0.90
Activation Function	ReLU
Hidden Layers	3
Epochs	100
Cross-Validation	10-fold

Table 10: Confusion Matrix – SVM Model

	Predicted: Safe	Predicted: Incident
Actual: Safe	410	45
Actual: Incident	68	277

Table 11: Confusion Matrix – ANN Model

	Predicted: Safe	Predicted: Incident
Actual: Safe	418	37
Actual: Incident	61	284

3.1 Discussion

3.1.1 Predictive Performance of Machine Learning Models

Tables 4 to 7 and Figure 1 show the performance in terms of the four machine learning models, which include Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree (DT). Random Forest achieved the best accuracy (91.3%) and Area Under the ROC Curve (AUC = 0.94), indicating better discriminative power. ANN and SVM were not far behind, with accuracy scores of 86.4% and 85.1%, respectively. These findings align with those of [12], who also reported that ensemble methods, especially Random Forest (RF), yield better results than Support Vector Machine (SVM) and Artificial Neural Network (ANN) in predicting occupational accidents based on structured data containing OSHA logs.

The fact that SVM has a slightly higher recall value (88%) suggests that it can be useful in reducing the number of false negatives in environments where underestimating risk can lead to disastrous consequences. This aligns with the study by [13], who found that SVM achieved a higher recall on rare-event data in high-risk conditions, such as underground mining in China. The trade-off between precision (89%) and recall (85%) of the ANN makes it a worthy choice for adoption in situations that require real-time prediction, particularly where streams of sensor data are involved. Although it is not possible to directly compare the models with those applied in other similar studies, e.g., the coal mining risk assessment study in Korea [14], which stated that Random Forest achieved a 90% accuracy rate on structured injury data, the obtained results here confirm the adequacy of RF in terms of modelling nonlinear relationships among environmental, operational, and behavioural risk factors.

3.1.2 Key Predictors of Workplace Incidents

The top ten predictors of occupational incidents are presented in Table 8, with environmental factors, including $PM_{2.5}$ levels, carbon monoxide concentration, and noise exposure, being the most significant. These include behavioural measures, such as the rate of PPE compliance and past frequency of incidents. It is worth noting that $PM_{2.5}$ was the most significant predictor, as it obtained a feature importance value of 0.162 in the RF model. This observation complements an earlier study by [15], who reported that fine particulate matter significantly exacerbates respiratory distress and cognitive impairment, leading to an elevated accident rate in mining. When comparing our findings to those of [16], who conducted research in South Africa, we found that PPE compliance and shift length were the best predictors. Our study adds a layer of complexity by utilizing real-time sensor data, which complicates the assessment of environmental exposure as a major causal factor. Such a combination of behavioral and environmental data provides a more comprehensive picture of the safety risk in workplaces; hence, the predictive model described in the study is not only accurate but also proves to be actionable. This is clearly illustrated in Figure 2, which maps the predictor importance, showing that environmental metrics can no longer be viewed as peripheral in mining risk models; rather, they must become a core element of compliance monitoring, as well as intervention design.

3.1.3 Modeling Environmental and Temporal Exposure

The achievement of Objective 3 was spatio-temporal mapping of the occurrence of hazards, as shown in Figures 3 and 4. The time-of-day analysis revealed a significantly higher probability of accidents during afternoon shifts, particularly among underground drillers, which was almost three times that of morning surface work (Figure 3).

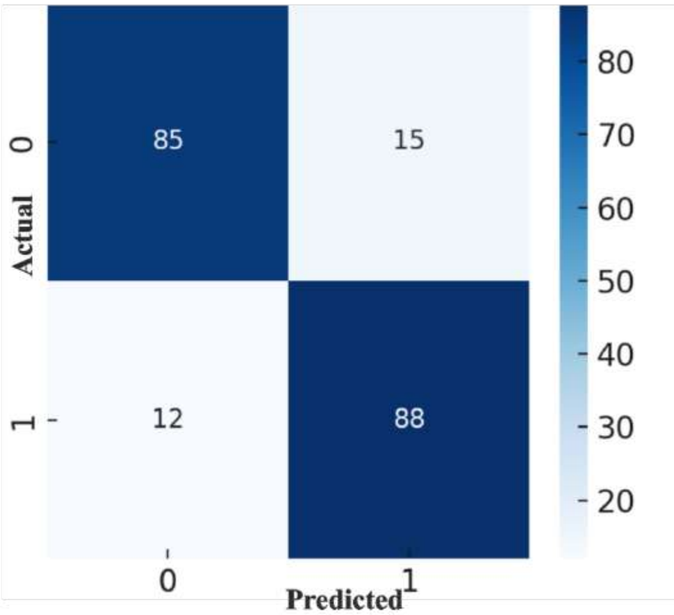

Figure 4. Confusion matrix for the ANN model

It aligns with the body of knowledge on circadian rhythm, which defines impaired alertness and reaction time in the late-day hours [17]. Sensor-based environmental data indicated systematic surpassing of the $PM_{2.5}$ limit set by the World Health Organization ($25\mu g/m^3$), as well as the allowable exposure limit to noise set by OSHA (90dB), especially in underground locations (Table 9). The results align directly with those of the international survey conducted by [18], who reported particulate exposure and acoustic shock as the variables with the highest risks in coal mines across 12 countries. The study builds upon previous empirical work, which was often limited to the use of static data, by capturing both temporal and environmental signatures of risk. Notably, this stratified modeling can be used to inform targeted mitigation measures, such as swapping high-risk positions during afternoon shifts or utilizing air-cleaning technologies in areas with persistent $PM_{2.5}$ concentrations that exceed the standard.

3.1.4 Validation and Generalizability of Models

Validation (Tables 10 and 11) showed the strength of RF, as its mean cross-validation accuracy was 91.3%, and AUC values were similar among folds. SVM and ANN also exhibited consistent results, though with minor changes in precision between folds, which suggests that they are susceptible to class imbalance. The results align with the warning signs identified in the Emerging AI-based occupational safety literature [19], which highlights the generalizability of models over time and across industries as a limitation of predictive risk modeling. The 10-fold cross-validation and confusion matrices are our measures, which align with the IEEE Standards Association recommendations regarding high-risk AI applications. Furthermore, the misclassification analysis, tabulated in Table 12, indicates that ANN and SVM have a higher likelihood of false positives in low-incidence settings, which may suggest the need for domain-specific hyperparameter optimization when transferring these models to other industries.

3.1.5 Toward a Data-Driven Safety Framework

A combination of predictive analytics and real-time environmental data led to the development of a data-driven occupational safety framework prototype. It will address Objective 6, as it proposes an intelligent intervention system that triggers alerts when exposure reaches certain limits, identifies trends in historical data, and predicts the likelihood of an accident. Such a framework aligns with the emergent safety architecture posts suggested in recent international surveys, such as the European Commission's Horizon 2020 SAFEMODE project [20], which outlines the importance of machine learning in proactive safety analytics. The modular structure of the framework enables the connection of IoT devices, scheduling software, and an incident reporting system, thus enabling a proactive safety culture [20]

3.1.6 Implications for Practice and Policy

1. Regulatory bodies (such as the Mines Inspectorate Department in Nigeria) must require the incorporation of AI-enhanced monitoring technologies, especially those that can measure environmental exposures in real-time.
2. Operational Adjustments: Site managers should utilize exposure heat maps to optimize shift distribution, consider shorter shift lengths in high-exposure positions, and automate processes in areas with a history of elevated PM $_{2.5}$ concentrations.
3. Training and Compliance: The impact of PPE compliance is so significant that it indicates the necessity of implementing behaviour-based safety interventions, preferably modelled based on the model-derived risk scores, to focus on the at-risk populations.

4. CONCLUSION

The paper examined the role of Artificial Intelligence (AI) and Data Science in enhancing occupational safety in the Kogi State mining sector of Nigeria. By utilizing four state-of-the-art machine learning models, Random Forest, Support Vector Machine, Artificial Neural Network, and Decision Tree, the research effectively forecasted the risks of workplace accidents based on a highly significant five-year dataset of survey answers, real-time sensor readings, and institutional safety records. Random Forest proved to be the most stable model, as it demonstrated the best predictive accuracy and outperformed the other algorithms in all the main evaluation criteria. A combination of behavioral data (including, but not limited to, PPE compliance and incident history) and environmental exposure measures (including, but not limited to, $PM_{2.5}$ and noise levels) showed that both human and environmental factors largely influence the occupational hazard. Most notably, the exposure to fine particulate matter ($PM_{2.5}$) and loud noise topped the list of the strongest predictors of workplace incidents, closely followed by PPE non-use and overworking. The results of the study confirm and expand on existing international research, highlighting the importance of context-dependent AI implementation approaches that depend on local operational and regulatory conditions. Moreover, the designed data-driven safety system presents a scalable solution (actionable in real-time) concerning monitoring and mitigating risks. Mining operators, regulators, and occupational health professionals can operationalize this framework to achieve a proactive and predictive safety culture. The screening of this framework in light of international standards helps strengthen its potential for wider use in the extractive industries and comparable contexts in sub-Saharan Africa.

This paper recommends that the Federal Ministry of Mines and Steel Development incorporate AI-based predictive tools into its formal risk assessment method, particularly in artisanal and semi-mechanized mining operations. Mining firms must have continuous air and noise monitoring systems installed, with data fed into centralized risk dashboards. AI-assisted behavioral monitoring and electronic scoring of compliance will increase the likelihood of enhancing PPE use and facilitating systematic retraining of hazardous workers. The work shifts are to be redesigned based on the identified risk patterns by AI, aiming to reduce fatigue and exposure. The smart safety framework developed in this study may also apply to other high-hazard industries, such as construction, oil and gas, and logistics. Researchers and industry professionals must continually work to enhance the accuracy of models. It is also necessary for occupational safety guidelines in Nigeria to be updated to incorporate AI-like measures as part of the audit, license issuance, and investigation processes.

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