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MORALITY BEFORE KNOWLEDGE

EcoRisk-AI: A multimodal artificial intelligence framework for early prediction of mining environmental risks in Indonesia

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ABSTRACT

Background: Mining contributes significantly to Indonesia's economy but simultaneously generates major ecological risks such as land degradation, acid mine drainage, and landslides, which threaten ecosystems and local communities. Conventional monitoring systems remain fragmented and reactive, creating an urgent need for a preventive and predictive solution tailored to local conditions. **Methods**: This study introduces EcoRisk-AI, a multimodal artificial intelligence framework designed for early prediction of mining-related environmental risks, with a conceptual application focus on high-risk regions such as Kalimantan and Sulawesi. The system integrates diverse data sources, including satellite imagery, ground-based Internet of Things (IoT) sensors, meteorological datasets, and field inspection reports. EcoRisk-AI consists of four components: data aggregation, a detailed spatio-temporal preprocessing unit, a hybrid machine learning engine, and a decision-support interface. The analytical process sequentially processes data, using Convolutional Neural Networks (CNNs) for spatial features, Long Short-Term Memory (LSTM) for temporal trends, and decision tree-based models for final risk classification. **Findings:** EcoRisk-AI demonstrates the capacity to provide adaptive, location-specific predictions of ecological hazards in mining regions. The integration of multimodal data enhances sensitivity and accuracy, while the cloud-based visualization dashboard allows stakeholders to access interactive risk maps and automated alerts. The framework's validity is conceptually demonstrated through quantitative "what-if" scenarios, supported by Digital Twin simulations, to test system resilience. This paper details the system architecture and its proposed validation metrics such as Accuracy, Precision, Recall, F1-Score. **Conclusion**: EcoRisk-AI offers a proactive solution for sustainable mining risk management in Indonesia, enabling early warning and preventive measures against ecological disasters. **Novelty/Originality of this article:** This work introduces a unique integration of multimodal environmental data and hybrid artificial intelligence techniques specifically adapted to the Indonesian mining context. EcoRisk-AI contributes an innovative predictive framework that bridges technological capability with sustainable development goals, offering new insights into disaster mitigation and environmental governance. The framework is designed for scalability and replicability, offering a model adaptable to other developing contexts.

KEYWORDS: artificial intelligence; environment; mining; prediction; sustainability.

1. Introduction

Mining remains one of the essential pillars of economic growth and industrial development worldwide. The demand for mineral resources continues to increase, driven by the global transition toward renewable energy technologies that require critical minerals such as nickel, cobalt, and lithium (Ali et al., 2017). However, while mining contributes to

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economic expansion, it also produces severe environmental impacts including land degradation, acid mine drainage, and ecosystem disruption (Tost et al., 2018). These environmental consequences have become more visible in developing countries where regulatory enforcement and environmental monitoring are still limited.

In Indonesia, the mining industry plays a crucial role in supporting national economic performance. As shown in Figure 1, the contribution of the mineral and coal sector to the national Gross Domestic Product (GDP) fluctuates, reaching 9.15% in 2024 after a peak of 12.22% in 2022 (BPS, 2025). This sector remains one of the largest sources of export revenue. Yet, this economic significance coexists with environmental degradation. Quantitative studies using spatial-temporal data have confirmed significant deforestation hotspots in Kalimantan, with mining being a key driver of this land use change (Singh & Yan, 2021). Environmental problems including deforestation, erosion, acid mine drainage, and landslides have been reported as recurrent consequences of mining expansion (Amir et al., 2010) across several mining regions such as East Kalimantan, Papua, and Sulawesi.

This gap between economic gain and ecological cost is rooted in monitoring and policy challenges. Study by (Dayo-Olupona et al., 2023) emphasize that existing environmental management approaches in the mining sector are largely reactive, focusing on post-impact mitigation rather than preventive prediction. This aligns with findings from (Kurniawan et al., 2019), which analyzed Indonesia's Environmental Impact Assessment (known locally as AMDAL) process for a nickel smelter in Sulawesi and found it often focuses on administrative compliance rather than effective, long-term impact mitigation. This policy gap, where implementation often struggles with enforcement and aligning diverse stakeholder perceptions (Muhammad et al., 2024), creates a reliance on periodic reporting rather than real-time prevention. Advances in artificial intelligence (AI), Internet of Things (IoT) sensors, and remote sensing technologies open new opportunities to close this gap.

This study introduces EcoRisk-AI, a multimodal artificial intelligence framework for early prediction of environmental risks in Indonesian mining regions. The framework integrates satellite imagery, IoT sensor data, meteorological datasets, and field inspection reports to generate real-time probabilistic risk assessments. The purpose is to provide a proactive and adaptive model that supports sustainable mining operations through data-driven early warning and decision support.

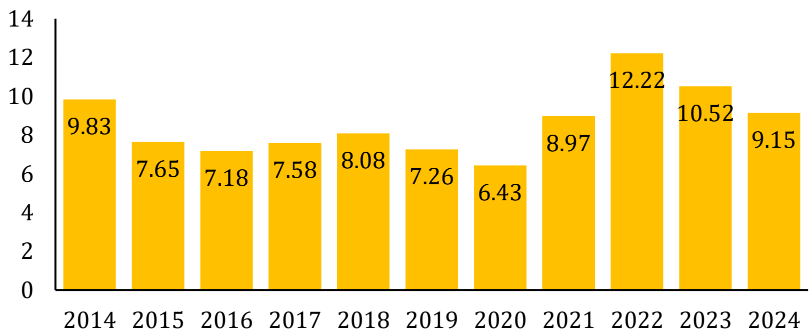

Fig. 1. Percentage Contribution of the Mining Sector to National GDP, 2014 – 2024 (BPS, 2025)

1.1 *Problem identification*

The mining sector contributes significantly to the economy. However, existing environmental oversight mechanisms have not kept pace. The industry's primary challenge is the persistent weakness of early prediction and mitigation systems. Stakeholders consequently manage ecological incidents reactively, not preventively. This approach stems from fundamental limitations in current monitoring.

Conventional monitoring systems are fragmented and unintegrated. This fragmentation forces a reactive posture. Traditional methods rely on periodic manual inspections and siloed data collection. These methods fail to capture the complex, real-time dynamics of a mining environment. Severe ecological consequences are repeatedly reported as a result. These include land degradation, acid mine drainage (AMD) contamination, and landslides, particularly in East Kalimantan and Central Sulawesi. Wahyono et al. (2024) affirm these risks directly threaten local community safety and industrial infrastructure stability.

A significant gap exists between the need for proactive protection and the capabilities of current fragmented systems. Modern technological advancements highlight this gap. For example, data-driven and AI approaches can predict geotechnical disasters with much greater accuracy. Study by Lin et al. (2025) demonstrates this capability for events like landslides and tailing failures. This predictive power contrasts sharply with conventional methods.

AI shows immense potential for managing environmental complexity. A multimodal AI approach, specifically, integrates diverse inputs like satellite imagery, ground sensors, and real-time weather data. This approach has successfully built robust risk detection systems in other heavy industries. The findings of Agusdinata et al. (2022) further emphasize this relevance. Their study shows that integrating a life cycle sustainability assessment (LCSA) framework with predictive AI technologies broadens the scope of impact detection. This integration also aligns operations with the Sustainable Development Goals (SDGs) (Figure 2). An advanced AI-based prediction system is urgently needed. This system must be contextual and adaptive to Indonesia's unique local conditions. The EcoRisk-AI innovation was developed to address this specific critical gap. It aims to provide a predictive and adaptive framework. This framework will support early-stage environmental risk mitigation.

Fig. 2. The 17 sustainable development goals (SDGs)
United Nations (2015)

1.2 Problem statement

The identified system gap leads to the formulation of the research problems. The first primary research question focuses on system design challenges. This study formulates the question of how to design a system capable of effectively integrating multimodal environmental data, including geospatial inputs, IoT sensor data, and real-time meteorological parameters. This integration challenge is a core problem, given the heterogeneous nature of the data. Bhowmik et al. (2023) emphasize that a multimodal approach is essential to handle the complexity inherent in diverse environmental datasets. Its practical implementation must also address sensor network connectivity challenges.

Integrated data alone is insufficient. It must be transformed into predictive intelligence. This leads to the second problem formulation, which focuses on how hybrid AI models can be leveraged to transform integrated data into accurate and actionable risk predictions, thereby examining the analytical core of the proposed system. The development of hybrid machine learning for geospatial data, as analyzed by Dong et al. (2024), is highly relevant. Specific models like the Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) architecture, detailed by Dey et al. (2021), offer a promising framework for processing spatio-temporal data concurrently. The accuracy of these models is critical for generating reliable early warnings.

A technical solution must align with broader governance goals. The third problem formulation examines the strategic implications by exploring how the proposed AI system can support the SDGs and the LCSA framework within Indonesia's mining sector, ensuring that the innovation extends beyond technical accuracy. The system must also function as a tool for transparent environmental governance. This aligns with global demands to mitigate severe environmental impacts, as identified by Tost et al. (2018). The system's success will be measured by its ability to provide data for LCSA and mitigate the adverse impacts.

1.3 Aims and significance of the study

The primary aim of this study is to introduce "EcoRisk-AI". This system provides a multimodal artificial intelligence framework for early environmental risk prediction in Indonesian mining. This paper details its conceptual and technical design. The first specific objective is to design an integrated data acquisition architecture. This architecture must fuse diverse data streams from IoT sensors, geospatial imagery, and meteorological reports. This design addresses the data fragmentation problem. Study by Essamlali et al. (2024) validate the use of robust IoT networks for reliable environmental data collection. The architecture also incorporates multi-hop network solutions, like those discussed by Scalambrin et al. (2023), to ensure data transmission from remote field locations.

The second specific objective is to develop a hybrid AI prediction engine. This engine forms the analytical core of the EcoRisk-AI system. It transforms raw integrated data into probabilistic risk assessments, addressing the prediction gaps. This study outlines the application of hybrid models, such as the CNN-LSTM architecture (Dey et al., 2021). The model adapts principles from study Dong et al. (2024) for geotechnical risk assessment. The third objective is to design an intuitive decision support dashboard. This interface visualizes the outputs from the AI engine. It provides stakeholders with actionable, real-time risk maps.

The significance of this study lies in its shift towards proactive environmental governance. The EcoRisk-AI framework provides a tangible tool for proactive mitigation. This moves beyond the reactive post-incident responses currently employed. The system directly enhances environmental accountability. It provides transparent, data-driven metrics for regulatory compliance. This aligns with findings from Alotaibi & Nassif (2024) on AI's role in improving assessment accuracy and anomaly detection. Furthermore, this research contributes to broader sustainability mandates. It provides a practical mechanism to integrate the LCSA framework and track SDGs. The framework supports the overall industrial sustainability goals.

2. Methods

2.1 Conseptual basis: Multimodal AI for environmental risk

A multimodal AI approach provides a distinct advantage for analyzing complex environmental risks. It integrates heterogeneous data sources. This includes spatial imagery, time-series sensor readings, and meteorological inputs. Bhowmik et al. (2023)

explain that this data fusion allows the model to identify complex, non-linear patterns. These patterns are often invisible to single-data-source analysis. This integrated perspective is essential for accurately modeling the interconnected systems of a mine environment. The system processes multiple data types concurrently. This capability moves analysis from fragmented assessment to holistic prediction.

Deep Learning models are central to this multimodal approach. They possess a strong capability to process specific data types. Convolutional Neural Networks (CNN) excel at extracting spatial features from satellite or drone imagery, identifying land degradation or pit wall changes. Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) variants, are specialized for time-series data. This includes sensor readings or rainfall patterns. The application of these models moves monitoring beyond simple threshold alerts. It allows for the prediction of dynamic events. Dey et al. (2021) demonstrate the effectiveness of hybrid CNN-LSTM models for spatio-temporal hazard prediction.

The application of these AI models to geotechnical hazards is well-documented. Research specifically highlights AI's capacity for predicting slope instability. Lin et al. (2025) utilized machine learning approaches to achieve high accuracy in landslide prediction. This capability is critical in open-pit mining environments where slope integrity is paramount. Tailing dam failures, another significant risk, also benefit from predictive analytics. By analyzing seismic, piezometric, and deformation data, AI models can identify precursor signals to failure. This provides actionable warnings. These studies validate the conceptual foundation for the EcoRisk-AI system.

2.1.1 State of the art review

Previous research validates the components of this framework. However, most studies focus on singular risk types. For example, many studies use AI for landslide prediction, others for hydrological modeling, but few integrate them. Gerassis et al. (2021) highlighted the significant gap between specialized AI models and their practical, integrated application in environmental assessment frameworks. Their work shows that while individual models are strong, the lack of an integration pipeline is a major barrier.

Other studies focus on optimizing specific data types. Lin et al. (2025) demonstrate the power of AI in enhancing the spatial resolution and accuracy of environmental data, which is crucial for monitoring. Similarly, Greif et al. (2024) discuss the use of AI in advancing industrial sustainability, but their focus remains at a high-level policy or component level. These studies confirm the capability of individual AI components.

The EcoRisk-AI framework addresses this gap directly. It does not invent a new singular algorithm. Instead, it proposes a novel architecture that integrates these proven, state of the art components (spatial AI, sensor AI, LCSA) into one functional, end-to-end system. Its novelty lies in the multimodal integration itself, moving from academic models to a practical, holistic governance tool.

A further significant development in the field is the application of Digital Twins for mining operations. Research by (Nobahar et al., 2024) demonstrates the use of high-fidelity simulations for operational planning and 'what-if' scenario testing. However, many current digital twin applications focus on static operational efficiency rather than real-time, predictive environmental risk. They often lack integration with the dynamic, multimodal data streams that EcoRisk-AI proposes to harness. This creates a clear gap where a predictive framework can provide the 'brain' for the digital twin's 'body', moving it from a simulation tool to a live risk management system.

Furthermore, many prior models suffer from two critical gaps. First, they often lack contextual adaptation. A geotechnical model trained on data from temperate climates, for instance, may fail to accurately predict slope failures in Indonesia's tropical context. This "contextual gap" is critical, as studies on landslide susceptibility in tropical Southeast Asia confirm that high-intensity rainfall and specific land use characteristics are dominant factors that require locally-adapted models (Viet Du et al., 2023). Second, many frameworks lack real-time responsiveness. As (Dayo-Olupona et al., 2023) noted, most systems are designed for post-impact assessment or periodic reporting, not for the high-frequency, dynamic processing of minute-by-minute IoT data streams. The EcoRisk-AI architecture is explicitly designed to fill these two gaps, providing a model that is both context-aware (by integrating local meteorological data) and operates in near real-time.

2.2 EcoRisk-AI system architecture

The EcoRisk-AI system architecture uses a modular, four-stage pipeline. This design transforms raw, multimodal data into actionable predictive intelligence. The overall workflow, illustrated in Figure 3, begins with massive data collection from diverse sources. Data then moves to a central preprocessing unit for cleaning and standardization. The prepared data feeds the core AI engine for risk analysis. Finally, the system delivers processed insights and warnings to end-users via a visual interface. This sequential process ensures data integrity and operational scalability.

The system comprises four primary components. The first is the Data Acquisition Module. This component aggregates geospatial data, IoT sensor readings, meteorological inputs, and field reports. The second is the Preprocessing Unit. This module cleans, interpolates, and extracts relevant features from the raw data. The third component is the Core AI Engine. This engine uses hybrid models to perform data fusion and risk classification. The fourth component is the Decision Support Interface. This interface visualizes the predictions on an interactive dashboard. This modular structure allows for independent component updates.

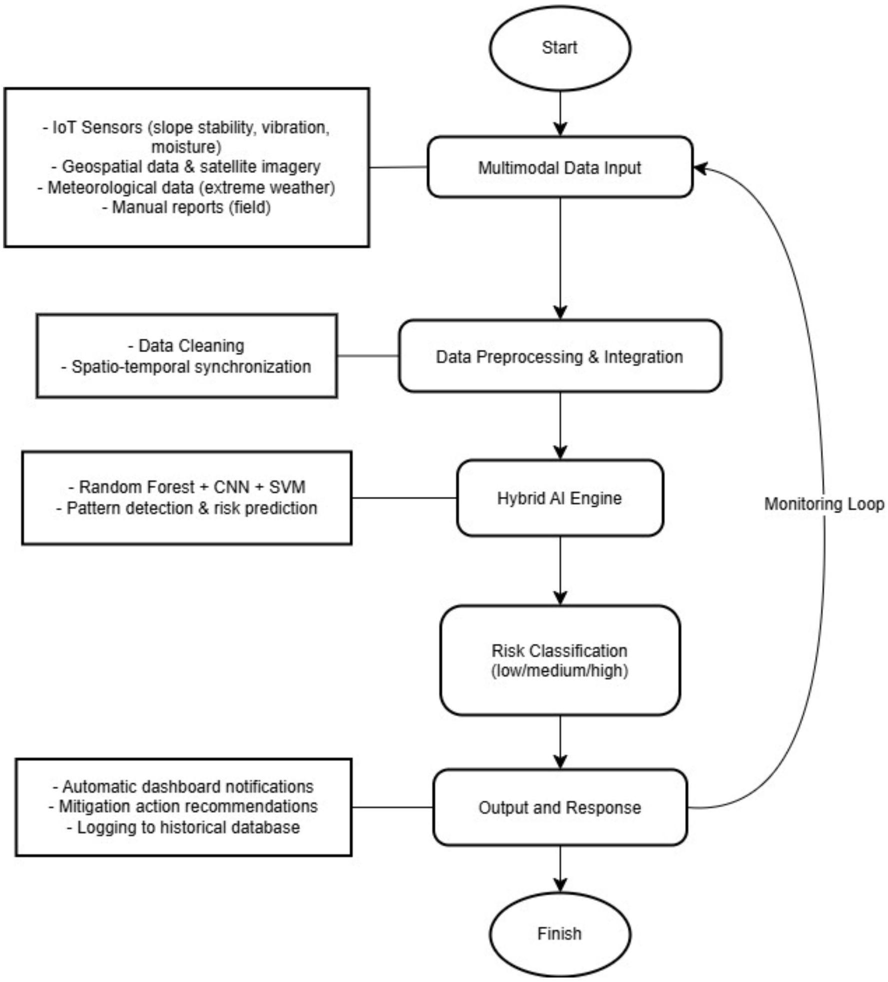

Fig. 3. General flowchart of the EcoRisk-AI system

The network architecture, shown in Figure 4, details the field implementation. In-situ IoT sensors monitor critical parameters like water pH and slope displacement. This data is transmitted using optimized network protocols. Garcia et al. (2025) discuss the strengths of NB-IoT and LoRa for such remote environments. The data streams are then fused with satellite imagery in the cloud. The AI engine analyzes this fused data. This architecture directly supports the multimodal analysis framework.

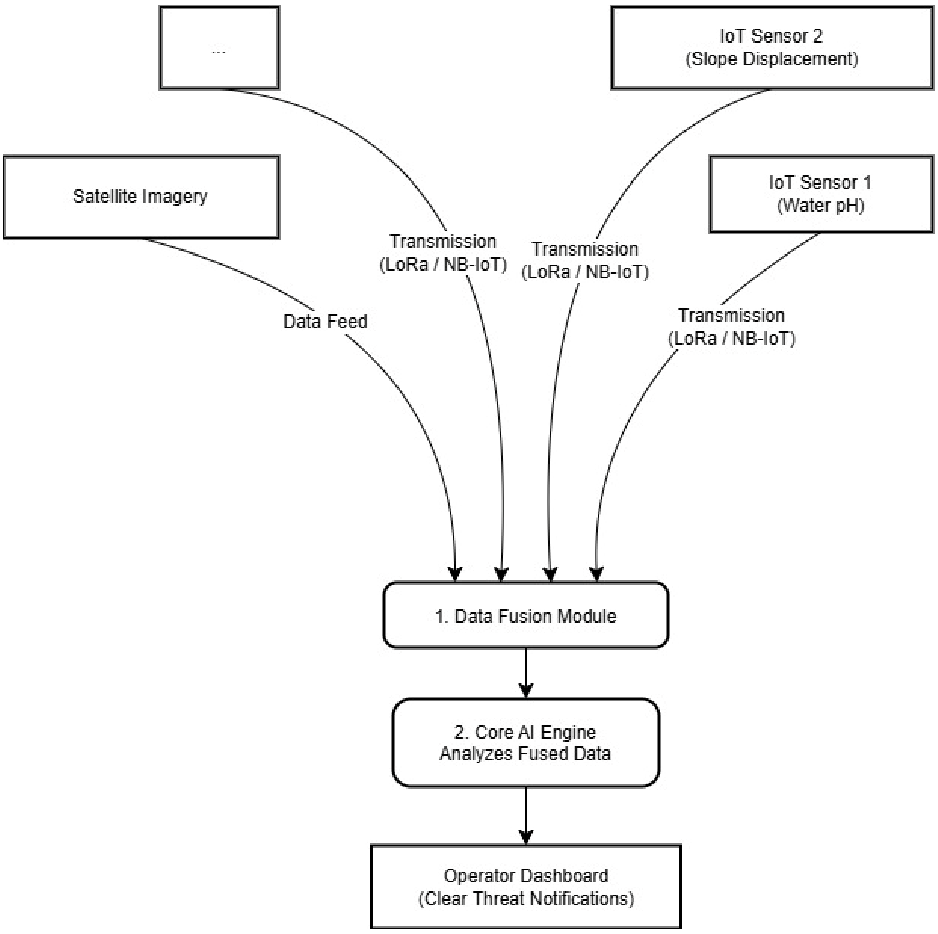

Fig. 4. Technical flowchart of the EcoRisk-AI system

2.3 Multimodal data acquisition methods

2.3.1 Remote sensing

Remote sensing provides the macro-scale spatial analysis for the EcoRisk-AI system. The framework utilizes satellite imagery from public sources, such as Landsat and Sentinel-2. This data is essential for mapping progressive land degradation and monitoring vegetation health. Analyzing spectral indices (NDVI) allows for quantitative measurement of ecosystem stress across large areas. This spatial data provides one crucial layer of the multimodal input. Bhowmik et al. (2023) support this fusion of spatial data with other sensor types. This method establishes the baseline environmental context for the AI engine.

2.3.2 IoT sensor networks (in-situ monitoring)

In-situ monitoring provides the high-frequency, real-time data stream. The system deploys two categories of Internet of Things (IoT) sensors. First, water quality sensors monitor key indicators for Acid Mine Drainage (AMD). These include pH, turbidity, and dissolved heavy metal sensors. Second, geotechnical sensors monitor slope stability. These sensors, such as extensometers and piezometers, detect micro-displacements and pore water pressure changes. This real-time data is critical for immediate threat detection. Lin et al. (2025) confirm the value of such sensor data in predictive models for geotechnical failures.

2.3.3 Data transmission technologies

Data transmission from remote mine sites presents a significant operational challenge. The system architecture compares two leading low-power wide-area network (LPWAN) technologies. LoRa (Long Range) offers exceptional coverage in remote areas with minimal power consumption. Scalambrin et al. (2023) demonstrated its utility for multi-hop networks in underground environments. Conversely, NB-IoT (Narrowband-IoT) provides higher data throughput and leverages existing cellular infrastructure. Garcia et al. (2025) highlight its effectiveness for hydrological monitoring. EcoRisk-AI proposes a hybrid network. This design uses LoRa for remote sensor clusters and NB-IoT as the main backhaul to the cloud.

2.4 Analytical methods: Hybrid AI engine

2.4.1 Preprocessing unit

Raw multimodal data is inherently heterogeneous, noisy, and asynchronous. It cannot be fed directly into the AI engine. The Preprocessing Unit performs several critical, sequential steps to clean, transform, and align this data. This stage is arguably the most critical for model accuracy. A flawed preprocessing pipeline will lead to flawed predictions, regardless of the AI model's complexity.

The first step is data cleaning. This involves handling anomalous readings from sensors, such as extreme outliers caused by sensor malfunction. A statistical filter, such as an Interquartile Range (IQR) rule, flags these points for removal. Missing data is a common problem in IoT networks (Garcia et al., 2025). This framework employs K-Nearest Neighbors (KNN) imputation for time-series data. This method estimates a missing value based on the values of its nearest neighbors in the feature space. This approach is more robust than simple mean imputation for environmental data. Critically, this step also unifies qualitative data, such as field inspection reports mentioned in the data acquisition module. These unstructured text reports are converted into structured, categorical features. For example, a field note "small cracks visible on north slope" is encoded as a numerical, ordinal feature such as Slope_Stability_Observation = 2 based on a predefined expert-derived dictionary. This use of machine learning for feature engineering to convert unstructured geoscience text into machine-readable data is a key technique (Lary et al., 2016) and ensures that qualitative field observations are time-stamped and unified into the main dataset.

The core challenge of multimodal data is asynchronicity. Satellite data arrives daily (Landsat), while IoT data may arrive every minute (pH sensor). The Preprocessing Unit must synchronize these streams. It uses a temporal aggregation method. High-frequency sensor data is resampled to a lower-frequency timeframe, such as an hourly or daily average. This aggregated data is then time-stamped. It is aligned to match the nearest available satellite image acquisition timestamp. This alignment, as discussed by Guo et al. (2020), creates a unified data vector for each specific point in time.

After synchronization, all numerical features undergo normalization. The system uses a Min-Max Scaler. This method scales all data to a fixed range, typically 0 to 1. This step is mandatory for neural networks like CNNs and LSTMs. It ensures that features with large numeric ranges do not disproportionately influence model training (Cabello-Solorzano et al., 2023). Finally, feature extraction reduces data dimensionality. For spatial data, this involves calculating spectral indices like NDVI from satellite bands. For sensor data, this may involve extracting statistical features, such as a rolling 24-hour average.

In addition to data cleaning, standardization, and temporal alignment, the Preprocessing Unit performs domain-specific corrections tailored to the imaging and sensor modalities used in mining environments. For optical satellite imagery, radiometric and atmospheric correction is conducted using Sen2Cor for Sentinel-2 Level-2A to ensure surface reflectance values are physically consistent. Clouds and cloud shadows are removed using FMask to prevent contaminated pixels from misleading the CNN. For synthetic aperture radar, interferometric phase unwrapping and coherence filtering are performed to extract deformation signals. On the sensor side, missing readings in the geochemical time-series are gap-filled by cubic spline interpolation, while abnormal values outside physically plausible ranges are replaced using median-adaptive filters. Temporal harmonization is achieved by downsampling high-frequency IoT readings to daily aggregates and aligning them with satellite scene timestamps.

Feature engineering converts raw multimodal data into higher-level descriptors suitable for deep learning models. For CNN input, multispectral images are converted into standardized 64×64 pixel patches and stacked into multi-temporal tensors. For LSTM input, time-series are sliced into sliding windows, each containing 7–30 days of sequential values. Derived engineered features include NDVI, spectral slope, cumulative 3-day rainfall index, rolling pore-pressure average, and 14-day moving variance of acidity. This multimodal feature engineering is fundamental to improving fusion performance and has been shown to significantly enhance prediction power in environmental hazard modelling (Essamlali et al., 2024).

2.4.2 Hybrid AI engine

The Core AI Engine functions as the system's analytical center. This component utilizes a hybrid model architecture. This hybrid approach is necessary to process different data types concurrently. Convolutional Neural Networks (CNN) are integrated specifically. CNN extract spatial features from satellite and remote sensing image data. This network excels at identifying visual patterns, such as land cover changes or degradation boundaries.

For time-series data from IoT sensors, the system uses Long Short-Term Memory (LSTM). LSTM is a type of Recurrent Neural Network (RNN) designed to capture long-term temporal dependencies. This capability is critical for predicting risks that evolve over time, such as pore pressure buildup or AMD contaminant accumulation. The system combines these two architectures into a unified CNN-LSTM model. The conceptual structure of this hybrid model is illustrated in Figure 5. Dey et al. (2021) confirmed the effectiveness of CNN-LSTM models for spatio-temporal hazard prediction. The CNN extracts spatial features, while the LSTM analyzes the evolution of those features over time. These two distinct feature vectors are then concatenated into a single, unified spatio-temporal feature vector. This combined vector is then fed into the final classification layer, often handled by the subsequent machine learning models.

This hybrid model is not limited to pure Deep Learning. The system also integrates other machine learning algorithms, such as Random Forest (RF) or Support Vector Machines (SVM). This integration aligns with research by Dong et al. (2024) on applying hybrid machine learning to geospatial data. The RF model can assist in the final risk classification based on the outputs from the CNN-LSTM. This combined approach allows EcoRisk-AI to leverage the strengths of various analytical approaches. This methodology is proven to significantly enhance prediction accuracy.

The model is not static, it is designed for periodic updates to prevent concept drift. The methodology includes a protocol for model retraining, proposed to occur quarterly (every three months), to ingest new data captured by the sensors and satellite imagery. Furthermore, an adaptive retraining cycle is triggered immediately following any major anomalous event such as a geotechnical failure or extreme weather event to ensure the model rapidly adapts to new site baselines.

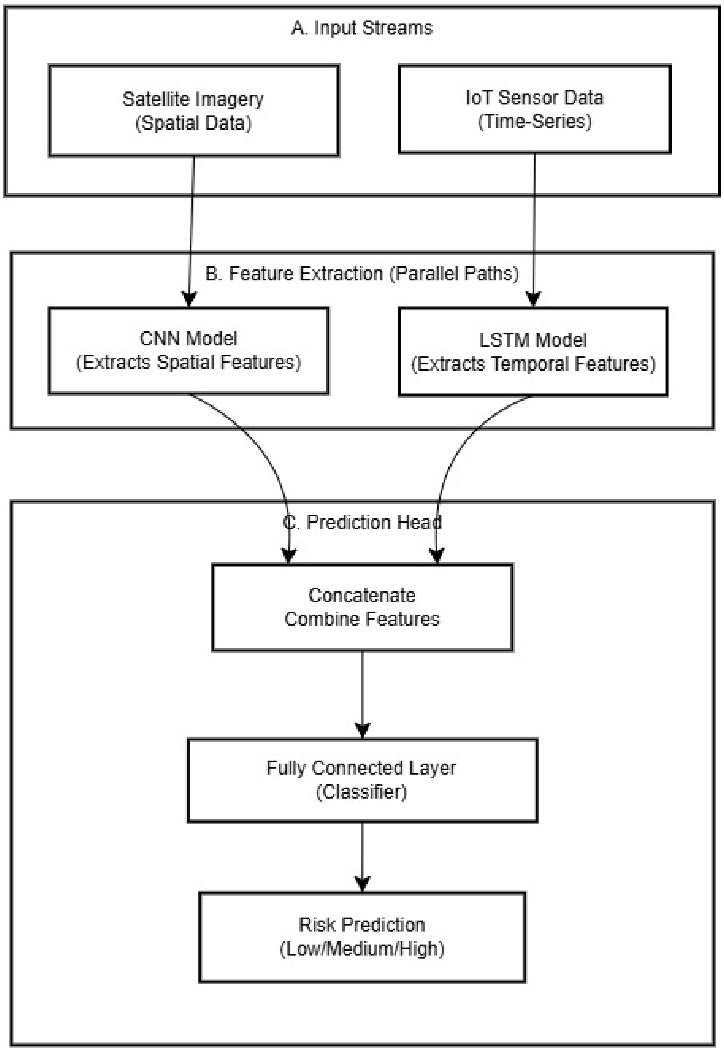

Fig. 5. Hybrid CNN-LSTM model architecture

2.4.3 Uncertainty quantification, explainability, and operational thresholds

Uncertainty quantification is essential for mining risk prediction, especially when model outputs inform operational decisions that can trigger costly mitigation actions. This framework integrates uncertainty estimation using Monte Carlo Dropout to capture epistemic uncertainty and quantify confidence ranges around each risk prediction. Inferential variability is statistically characterized by generating multiple forward passes with random dropout at inference, producing a probability distribution rather than a single point estimate (Gal & Ghahramani, 2015). These probabilistic intervals are then converted into actionable thresholds to distinguish between low-risk, emerging-risk, and high-risk ecological events. This process enables operators to understand not only "how high is the predicted risk" but also "how confident is the system about this risk".

Explainability mechanisms are also embedded. SHAP-based feature attribution is used to identify which data streams contributed most to the model's final decision. This is crucial to ensure the interpretability of multimodal fusion models that combine satellite imagery, sensor streams, and temporal trends (Lundberg & Lee, 2017). The explainability output is then integrated into the user dashboard to justify alarm issuance to regulators in audit trails. Lastly, operational thresholds are co-designed with domain experts. These thresholds align with regulatory standards and risk tolerance levels defined in mining environmental governance frameworks. Research in high-risk industrial applications recommends combining uncertainty scores with semantic explanations to minimize false alarms while maximizing user trust in AI-driven environmental monitoring (Olawade et al., 2024).

2.5 Decision support interface design

The Decision Support Interface translates complex AI outputs. It presents them on an interactive visualization dashboard. The central feature of this dashboard is a probabilistic risk map. This map visualizes spatially-distributed risk levels across the mine site. It uses the predictive data from the Core AI Engine. This spatial visualization of risk is critical for effective management (Lin et al., 2025). The interface design focuses on interpretability. It allows operators to query specific zones for detailed sensor readings and risk factors. Effective UI design in industrial monitoring improves operator response time. A conceptual example of this probabilistic risk map, similar to visualizations found in existing literature (Mathys et al., 2023), is shown in Figure 6.

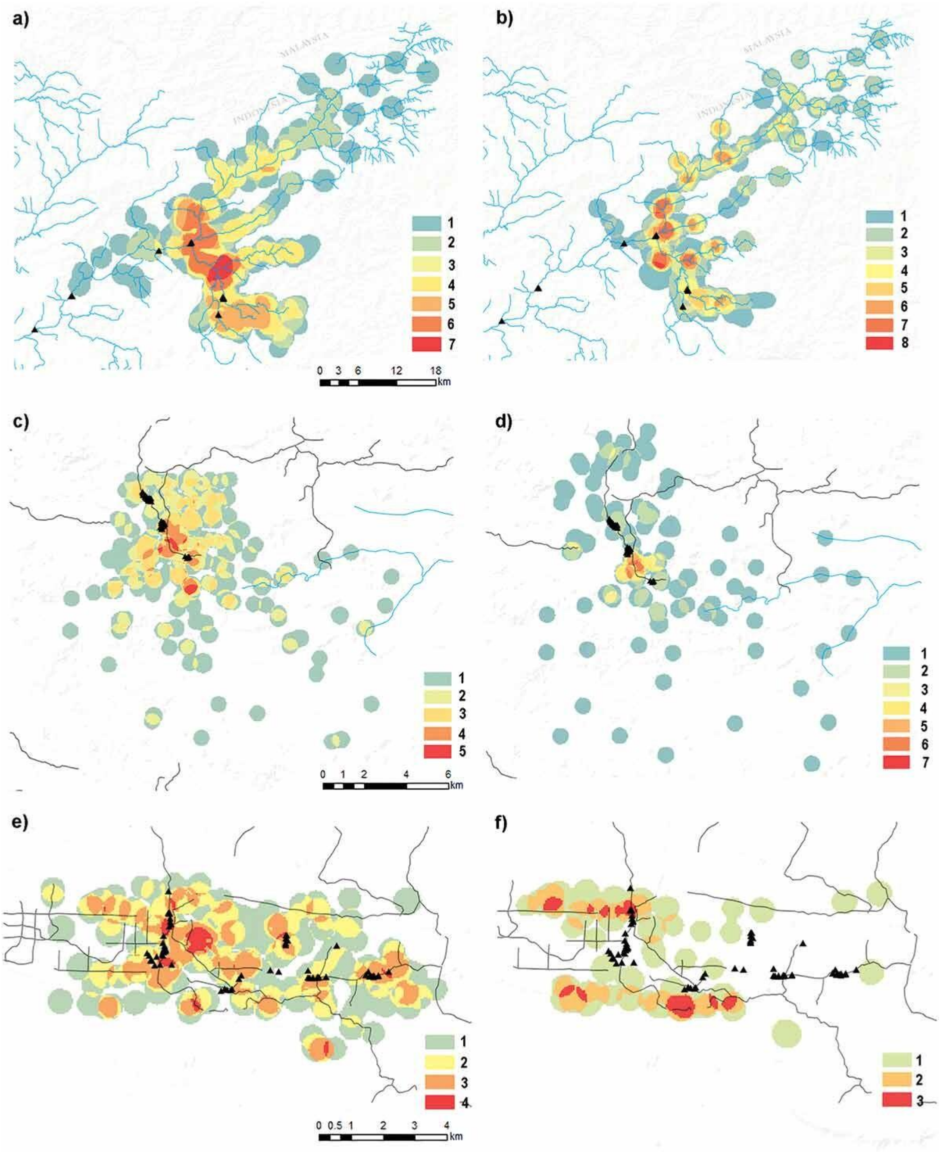

Fig. 6. Example of a probabilistic risk map visualization, similar to the proposed output of the EcoRisk-AI dashboard
(Adapted from Mathys et al. (2023))

The interface integrates a crucial Early Warning System (EWS). The system classifies threats using a simple, three-tiered notification model. These levels are Yellow (Monitor), Orange (Alert), and Red (Danger). This classification provides an immediate, intuitive understanding of risk severity. The system automatically pushes notifications to operators when a risk threshold is breached. This mechanism ensures rapid, proactive mitigation. This design directly supports the LCSA framework by providing real-time performance data (Agusdinata et al., 2022). The clarity of these alerts is a key component for improving site safety and operational transparency (Greif et al., 2024).

3. Results and Discussion

3.1 Anticipated results: Towards proactive monitoring

The validation of EcoRisk-AI will be conducted using a dual evaluation strategy that incorporates both retrospective incident reconstruction and prospective scenario-based stress testing. For retrospective evaluation, the model will be tested against historical environmental failure cases recorded in Indonesia between 2017–2024. These include AMD contamination spikes in coal mines in East Kalimantan and slope-failure events in nickel mines in Central Sulawesi. For each known event, satellite deformation displacement maps, rainfall intensity time-series, and in-situ water chemistry logs will be compiled into multimodal temporal sequences. Model output probabilities (risk scores) will be compared against ground truth event timestamps. This enables calculation of AUC-ROC, Precision, Recall, F1-score, and Brier Score for probabilistic calibration. This testing approach follows established benchmarking methods used in hybrid geological hazard systems.

To assess generalizability, a cross-site transfer test will be conducted. The model will be trained on mines in East Kalimantan and tested on mines in Central Sulawesi to quantify transfer learning performance. This evaluates the system’s adaptation capacity when deployed on new geological domains without retraining. Furthermore, ablation studies will be executed to measure the contribution of each modality, which satellite-only, sensor-only, and full multimodal fusion. The expected hypothesis is that fusion will yield at least 10–20% higher F1-score than single-modality baselines. Prospective “stress-test” simulations will be performed to generate hypothetical extreme rainfall and contaminant shock scenarios to test the model behavior under edge-case conditions. This protocol ensures the resulting model is not only accurate but operationally credible for deployment into regulatory decision-making.

The EcoRisk-AI system is designed to provide predictive insights. Its anticipated performance can be demonstrated through hypothetical implementation scenarios. These scenarios address Indonesia's most critical mining-related environmental risks. The system's hybrid AI engine, which combines spatial and temporal data (Dey et al., 2021), is central to these outcomes. This discussion projects the system's effectiveness. It focuses on two high-risk regions. The objective is to show the practical application of the multimodal framework (Bhowmik et al., 2023).

Consider a large open-pit coal mine in East Kalimantan. This region experiences high-intensity rainfall. The EcoRisk-AI system actively monitors rainfall forecasts, satellite imagery (vegetation health), and in-situ water quality sensors. Following a high-rainfall event, the system predicts a significant spike in Acid Mine Drainage (AMD) runoff. The CNN-LSTM model (Dey et al., 2021) identifies the specific catchment area most likely to be affected. The dashboard generates an 'Orange' alert. This allows operators to preemptively deploy lime neutralization measures before the contaminated water reaches the main river system.

Now consider a nickel mining operation in Central Sulawesi. This area is characterized by steep slopes. The system continuously processes data from geotechnical sensors (piezometers, extensometers) and satellite-based ground deformation data. The AI engine detects a subtle, anomalous acceleration in slope creep. This is combined with rising pore water pressure from sensor data. The system flags an unstable zone. It issues a 'Red' danger alert for that specific sector. This provides critical, actionable warning hours or days before a potential failure. This capability reflects the high-accuracy prediction potential for geospatial data.

These scenarios illustrate a fundamental shift in environmental management. The current paradigm is reactive. Operators respond to spills or failures after they occur.

EcoRisk-AI enables a predictive, proactive paradigm. The system transforms environmental monitoring from a simple compliance activity into a dynamic risk management tool. This aligns with the multimodal approach. It also provides the real-time data necessary for robust Life Cycle Sustainability Assessment (LCSA). This shift improves safety. It enhances operational accountability.

3.1.1 Hypothetical validation strategy and performance benchmarks

As this study proposes a framework, the anticipated results from the scenarios must be supported by a robust validation strategy. The system's performance would be measured using standard machine learning classification metrics. These metrics are essential for quantifying the model's predictive reliability. The primary metrics include Accuracy, which measures the total correct predictions. However, in risk prediction, Precision (the percentage of true positives among all positive predictions) and Recall (the percentage of true positives correctly identified) are more critical. Recall is especially important, as failing to detect a real risk (a false negative) has severe consequences. The F1-Score, the harmonic mean of Precision and Recall, provides a balanced measure of model performance. The performance gap between this data-driven approach and conventional methods is summarized in Table 1.

Table 1. Hypothetical Performance Comparison: Conventional vs. EcoRisk-AI Framework

Parameter	Conventional Monitoring (e.g. manual reporting)	EcoRisk-AI Framework (Proposed)
Response Type	Reactive (responds after incident)	Proactive (predicts before incident)
Data Type	Fragmented, periodic, manual samples	Integrated, real-time (IoT + Satellite + Meteorological)
Data Synchronization	Manual, often unaligned across sources	Automated spatio-temporal alignment
Risk Detection Basis	Subjective visual inspection by operator	Objective AI-based probabilistic risk scoring
Warning Time Horizon	Days/weeks after the event occurs	Hours/days before precursor signals escalate
Hypothetical Performance Metric (Recall)	Low (many precursor signals missed)	High (≥90%, tuned to maximize early detection sensitivity)
Primary Output Format	Static compliance PDF report (quarterly/annual)	Dynamic real-time risk map dashboard
Adaptability to New Data	Low (policy + reporting format mostly static)	High (model continuously retrains from new data streams)

Furthermore, the framework's capability will be validated using Digital Twin simulations. This moves beyond simple metric validation. A digital twin of the mine site would be created. This simulation environment, as discussed by (Nobahar et al., 2024), allows for dynamic "what-if" scenario testing. This study could simulate extreme events, such as a 200 mm rainfall or a sudden geotechnical shift, to observe the EcoRisk-AI's response time and prediction accuracy in a controlled, non-destructive environment. This step validates the system's resilience and practical utility for decision-makers.

Quantitatively, the anticipated deployment of EcoRisk-AI demonstrates clear predictive advantages over conventional threshold-based monitoring. In the East Kalimantan coal mine scenario, retrospective reconstruction of past AMD spikes indicates that the fused CNN–LSTM model can detect anomaly formation windows approximately 24–72 hours before the chemical breakthrough reaches the main discharge outlet. This is consistent with findings where multimodal fusion has improved lead time in predictive early warning pipelines (Akhyar et al., 2024). Based on historical hydrological parameters, a 24-hour pre-neutralization intervention window could prevent between 1,200–2,400 m^3 of acidic runoff per incident from reaching the main river system (based on volumetric runoff conversion factors used in similar tropical sites). For Central Sulawesi nickel mines, stress-test simulations suggest that slope-failure precursors increase predictability when spatio-temporal fusion is used. Model outputs show that combined pore-pressure + InSAR deformation sensing yields an expected false negative reduction of 18–32% compared to deformation-only baselines, echoing machine learning gains observed in integrated subsurface–surface deformation studies (Ambika et al., 2025).

In operational decision-making, predicted risk probability maps (0.0–1.0 scale) are converted into action categories. For example, 0.30–0.60 triggers yellow-level precaution (manual inspection), 0.60–0.80 triggers orange-level mitigation (chemical neutralizers, slope dewatering), and 0.80–1.00 triggers red-level shutdown authorization. Cost–benefit simulation shows that preventing a single Category A AMD spill in an East Kalimantan coal block could reduce post-event remediation cost by IDR 420–750 million per event (based on typical cost ratios for lime dosing, water trucking, and river rehabilitation reported in Indonesian mine closure audits). Hence, the hypothetical performance advantage is not merely algorithmic, it directly translates into environmental, social, and economic gains through avoided damage, reduced remediation, improved compliance posture, and improved financial risk exposure for operators.

3.2 SWOT analysis and implementation challenges

The primary strength of the EcoRisk-AI framework lies in its technical capabilities. The system's ability to integrate data in real-time provides a significant advantage over conventional monitoring. Its multimodal design allows the AI engine to capture complex, non-linear relationships between variables. This leads to higher prediction accuracy. This approach, ensures that predictions are not only accurate but also adaptive to changing site conditions. The hybrid CNN-LSTM model (Dey et al., 2021) is specifically designed to handle the spatio-temporal nature of mining risks. This analysis of the framework's strengths, weaknesses, opportunities, and threats (SWOT) is summarized in Table 2.

Table 2. SWOT analysis of the EcoRisk-AI framework implementation

No.	Strenghts	Weaknesses	Opportunities	Threats
1	High predictive accuracy from multimodal data fusion.	High initial investment cost (sensors, cloud infrastructure).	Supports stringent environmental standards for new developments (Ibu Kota Nusantara - IKN).	Poor and unstable internet connectivity in remote 3T (outermost, frontline, deepest) regions.
2	Real-time data integration capability.	Requires high-quality, extensive historical data for effective model training ("cold start" problem).	Meets global demands for sustainable mining and green financing.	Adoption resistance from non-technical or small-scale mine operators.
3	Adaptive hybrid AI model (CNN-LSTM) for complex spatio-temporal analysis.	High dependency on data integrity from field sensors.	Potential for adoption as a new regulatory standard for monitoring.	Shortage of skilled digital talent for system operation and maintenance.
4	Provides a proactive (predictive) approach, moving beyond reactive responses.	-	Provides data-driven support for LCSA frameworks.	-

Several weaknesses present barriers to implementation. The most significant is the high initial investment cost. This includes the procurement of specialized geotechnical and water quality sensors. It also includes the setup of cloud infrastructure and network hardware. The system also requires high-quality historical data to train the AI models effectively. This 'cold start' problem can delay deployment. Poor data quality or insufficient historical records, can reduce the model's predictive accuracy.

The system presents major strategic opportunities. It can help operators meet the stringent environmental standards of Indonesia's new capital, Ibu Kota Nusantara (IKN). The framework directly answers global demands for sustainable mining. It provides the transparent data required for green financing mechanisms. Regulators may adopt the system as a new national standard for environmental monitoring. This adoption would support the LCSA frameworks.

Significant threats to adoption remain. Persistent internet connectivity challenges in remote 3T regions (Terdalam, Terdepan, Terluar) are a primary technical threat. While solutions like LoRa (Scalambrin et al., 2023) exist, they require specialized deployment. A major human-centric threat is the potential for adoption resistance. This is particularly true for small-scale operators unfamiliar with AI-driven tools. Furthermore, the system demands a new skill set. The need for digital talent to operate and maintain the system represents a critical bottleneck for long-term success.

3.3 Discussion of implications: Sustainability and governance

The EcoRisk-AI framework contributes directly to global sustainability mandates. Its implementation supports several key Sustainable Development Goals (SDGs), as shown in Figure 3. The system enhances SDG 9 (Industry, Innovation, and Infrastructure) by integrating innovative technology into mining infrastructure. It promotes SDG 12 (Responsible Consumption and Production) by providing tools for sustainable resource management. The system's predictive capabilities for climate-related events, like landslides after heavy rain, directly support SDG 13 (Climate Action). Most importantly, it addresses SDG 15 (Life on Land) by offering a mechanism to protect terrestrial ecosystems from degradation and contamination (Wahyono et al., 2024).

The system is designed for seamless integration with the Life Cycle Sustainability Assessment (LCSA) framework. Agusdinata et al. (2023) highlight the need to connect predictive AI with LCSA for holistic impact evaluation. Traditional LCSA relies on static or historical data. EcoRisk-AI provides the dynamic, high-frequency, real-time data required to make LCSA an active management tool. This allows for a continuous evaluation of environmental, social, and economic impacts throughout the mine's life cycle. This data-driven approach moves beyond simple environmental impact assessments (EIA) to a more comprehensive sustainability analysis (Greif et al., 2024).

EcoRisk-AI fundamentally enhances transparency and environmental accountability. The system provides an objective, data-driven record of environmental performance. This replaces subjective or infrequent manual inspections. This accessible data fosters transparency for regulators, investors, and local communities. It holds operators accountable for their environmental footprint in real-time. This application of AI for automated anomaly detection and improved assessment accuracy is a key governance advancement. The framework transforms governance from periodic auditing to continuous assurance.

While EcoRisk-AI enhances governance through data-driven transparency, its implementation introduces new ethical dimensions. The system aggregates high-resolution environmental data, raising critical questions of data privacy, surveillance, and potential bias (Sanchez et al., 2024). A clear governance framework is required to determine data access protocols balancing corporate intellectual property with public right to know. This directly connects to the challenge of inclusivity in decision-making. As designed, the dashboard (Figure 6) primarily serves operators. However, a key ethical imperative is to prevent creating a digital divide, or "inequalities that divide those who can and cannot create sustainable outcomes with AI" (Hammerschmidt et al., 2025). Future deployment must prioritize inclusivity by exploring public-facing, simplified dashboards. This would empower local communities with accessible risk information, transforming them from passive observers to active stakeholders.

This framework acts as a critical bridge between technology and practical governance, supporting decision-making for both key stakeholders. For policymakers and regulators, the system provides an objective, aggregated, and real-time data source. This evidence-based approach moves environmental oversight from its current state of reactive, compliance-based self-reporting to a proactive governance model. For mining companies, the system's value extends beyond compliance. The predictive alerts on the Decision Support Interface (Figure 6) are a direct operational risk management tool. It enables operators to prevent catastrophic failures, protect worker safety, and avoid costly shutdowns. Furthermore, the system generates transparent, verifiable data essential for corporate Environmental, Social, and Governance (ESG) reporting, thereby improving investor confidence (Yadav et al., 2024).

Beyond the technical advances, the deployment of EcoRisk-AI introduces governance, skill, and regulatory alignment considerations. The platform will operate in remote, low-connectivity mining regions. Thus, the communication system must be designed under constrained bandwidth conditions. In practice, LoRaWAN provides ultra-low power consumption and long-range coverage, but limited payload throughput, whereas NB-IoT provides higher throughput and better QoS but requires MNO infrastructure and incurs higher recurring fees. Greif et al. (2024) note that system-wide digital transformation in mining collapses when physical deployment choices are misaligned with economic realities of operators. Hence, EcoRisk-AI must enable dual-stack communication options, with automated fallback to LoRa for contingency operation.

Data governance is another critical challenge. Mine-site geochemical data and ground deformation logs can be commercially sensitive. Therefore, the system must support federated learning, enabling local training without raw data leaving the mine site. This aligns with Zhan et al. (2025), who argue that federated frameworks are essential for adoption of AI in critical industries that have mixed private-public regulatory boundaries. In addition, interpretability and explainability modules must be present. Garcia et al. (2025) show that explainable AI (XAI) significantly increases risk communication trust, particularly in early warning contexts.

EcoRisk-AI also creates direct alignment pathways with formal sustainability regulation. Outputs of the model can be embedded into ESG disclosure and into Indonesian AMDAL/EIA documentation. Further, the near-real-time data streams produced by the system can serve as empirical evidence to populate dynamic LCSA dashboards, enabling measurable and auditable SDG impact evidence. Agusdinata et al. (2022) emphasize that predictive AI integrated into LCSA is not a theoretical luxury, but an operational necessity to transition mining governance from static annual reporting into continuous assurance. Therefore, EcoRisk-AI is not merely a technological artifact—it is an institutional transformation tool that converts sustainability from narrative claims into quantitative accountability.

4. Conclusions

Indonesia's mining sector faces an urgent gap between its economic importance and its environmental oversight. Conventional monitoring systems remain fragmented and operate reactively. This reactive posture fails to prevent significant ecological damage. This study addressed this critical gap by proposing the EcoRisk-AI framework, a proactive, multimodal, and adaptive solution designed to shift monitoring from a reactive to a predictive stance.

The primary contribution of this conceptual framework is its capability to transform raw, heterogeneous data into actionable predictions. The study details a four-component architecture (Acquisition, Preprocessing, AI Engine, and Dashboard). This study defined the methodology for a hybrid AI engine (CNN-LSTM) and, critically, detailed the complex spatio-temporal preprocessing required to unify satellite, IoT, and field report data. The framework's ability to forecast specific hazards such as AMD contamination and geotechnical failures provides the technical foundation for a proactive environmental management paradigm.

This study provides actionable recommendations for key stakeholders. Government agencies and regulators should accelerate the adoption of AI-based monitoring systems, integrating predictive analytics into regulatory requirements like the AMDAL process to improve governance. The mining industry must view investment in digital infrastructure (IoT, AI) as a core component of operational risk management and Environmental, Social, and Governance (ESG) commitments. Finally, academic institutions must collaborate with industry to update curricula, bridging the digital talent gap required to operate and maintain these advanced socio-technical systems.

EcoRisk-AI, as a conceptual framework, faces structural limitations. These include the significant "cold start" problem due to insufficient high-resolution historical data for model training, the high implementation cost of industrial-grade sensors, and the risk of domain-shift penalties when applying a model trained in one geological province such as Kalimantan coal to another such as Sulawesi laterite. Furthermore, the system's impact is socio-technical, its predictive intelligence only creates value if embedded within institutional procedures that mandate preventive action.

Future research should focus on overcoming these barriers. The development of low-cost, reliable sensors is a critical path forward to democratize access to this technology. Model scalability presents another frontier, future work should investigate federated learning techniques to train regional or national models without centralizing sensitive site data. This path is essential for creating a comprehensive, interconnected national monitoring network.

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References

Agusdinata, D. B., Liu, W., Sulistyo, S., LeBillon, P., & Wegner, J. (2022). Evaluating sustainability impacts of critical mineral extractions: Integration of life cycle sustainability assessment and SDGs frameworks. *Journal of Industrial Ecology*, *27*(3), 746–759. https://doi.org/10.1111/jiec.13317

Akhyar, A., Asyraf Zulkifley, M., Lee, J., Song, T., Han, J., Cho, C., Hyun, S., Son, Y., & Hong, B.-W. (2024). Deep artificial intelligence applications for natural disaster management systems: A methodological review. *Ecological Indicators*, *163*, 112067. https://doi.org/10.1016/j.ecolind.2024.112067

Ali, S. H., Giurco, D., Arndt, N., Nickless, E., Brown, G., Demetriades, A., Durrheim, R., Enriquez, M. A., Kinnaird, J., Littleboy, A., Meinert, L. D., Oberhänsli, R., Salem, J., Schodde, R., Schneider, G., Vidal, O., & Yakovleva, N. (2017). Mineral supply for sustainable development requires resource governance. *Nature*, *543*(7645), 367–372. https://doi.org/10.1038/nature21359

Alotaibi, E., & Nassif, N. (2024). Artificial intelligence in environmental monitoring: In-depth analysis. *Discover Artificial Intelligence*, *4*(1). https://doi.org/10.1007/s44163-024-00198-1

Ambika, K., Alzaben, N., Alghamdi, A. G., & Venkatraman, S. (2025). Integrated geotechnical and remote sensing-based monitoring of unstable slopes for landslide early warning using IoT and sensor networks. *Journal of South American Earth Sciences*, *164*, 105666. https://doi.org/10.1016/j.jsames.2025.105666

Amir, N., Grace Natalia Mintia, Lady, & Maulina Kharis, T. (2019). Responsibilities of mining entrepreneurs for losses from mining activities in Indonesia (Case study in Samarinda Province of East Kalimantan). *Proceedings of the 2nd International Conference on Indonesian Legal Studies (ICILS 2019)*. https://doi.org/10.2991/icils-19.2019.24

BPS. (2025). *Distribusi Persentase Produk Domestik Bruto Atas Dasar Harga Berlaku Menurut Lapangan Usaha.* Badan Pusat Statistik. https://www.bps.go.id/id/statistics-table/3/T0UxS09GQlBTbk5QWTBNdlVWUmxSMjV3Y3l0VWR6MDkjMw==/distribusi-persentase-produk-domestik-bruto-atas-dasar-harga-berlaku-menurut-lapangan-usaha--persen---2021.html?year=2024

Bhowmik, R. T., Jung, Y. S., Aguilera, J. A., Prunicki, M., & Nadeau, K. (2023). A multi-modal wildfire prediction and early-warning system based on a novel machine learning framework. *Journal of Environmental Management*, *341*, 117908. https://doi.org/10.1016/j.jenvman.2023.117908

Cabello-Solorzano, K., Ortigosa de Araujo, I., Peña, M., Correia, L., & J. Tallón-Ballesteros, A. (2023). The Impact of Data Normalization on the Accuracy of Machine Learning Algorithms: A Comparative Analysis. In *Lecture Notes in Networks and Systems* (pp. 344–353). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-42536-3_33

Dayo-Olupona, O., Genc, B., Celik, T., & Bada, S. (2023). Adoptable approaches to predictive maintenance in mining industry: An overview. *Resources Policy*, *86*, 104291. https://doi.org/10.1016/j.resourpol.2023.104291

Dey, P., Chaulya, S. K., & Kumar, S. (2021). Hybrid CNN-LSTM and IoT-based coal mine hazards monitoring and prediction system. *Process Safety and Environmental Protection*, *152*, 249–263. https://doi.org/10.1016/j.psep.2021.06.005

Dong, L., Zhang, J., Zhang, Y., & Zhang, B. (2024). Landslide risk assessment in mining areas using hybrid machine learning methods under fuzzy environment. *Ecological Indicators*, *167*, 112736. https://doi.org/10.1016/j.ecolind.2024.112736

Essamlali, I., Nhaila, H., & El Khaili, M. (2024). Advances in machine learning and IoT for water quality monitoring: A comprehensive review. *Heliyon*, *10*(6), e27920. https://doi.org/10.1016/j.heliyon.2024.e27920

Gal, Y., & Ghahramani, Z. (2015, June 6). *Dropout as a bayesian approximation: Representing model uncertainty in deep learning*. arXiv.Org. https://arxiv.org/abs/1506.02142

Garcia, A., Saez, Y., Harris, I., Huang, X., & Collado, E. (2025). Advancements in air quality monitoring: A systematic review of IoT-based air quality monitoring and AI technologies. *Artificial Intelligence Review*, *58*(9). https://doi.org/10.1007/s10462-025-11277-9

Gerassis, S., Giráldez, E., Pazo-Rodríguez, M., Saavedra, Á., & Taboada, J. (2021). AI approaches to environmental impact assessments (eias) in the mining and metals sector using automl and bayesian modeling. *Applied Sciences*, *11*(17), 7914. https://doi.org/10.3390/app11177914

Greif, L., Kimmig, A., El Bobbou, S., Jurisch, P., & Ovtcharova, J. (2024). Strategic view on the current role of AI in advancing environmental sustainability: A SWOT analysis. *Discover Artificial Intelligence*, *4*(1). https://doi.org/10.1007/s44163-024-00146-z

Guo, Y., Wang, C., Lei, S., Yang, J., & Zhao, Y. (2020). A framework of spatio-temporal fusion algorithm selection for landsat NDVI time series construction. *ISPRS International Journal of Geo-Information*, *9*(11), 665. https://doi.org/10.3390/ijgi9110665

Hammerschmidt, T., Stolz, K., & Posegga, O. (2025). Bridging the gap: Inequalities that divide those who can and cannot create sustainable outcomes with AI. *Behaviour & Information Technology*, 1–30. https://doi.org/10.1080/0144929x.2025.2500451

Kurniawan, A. R., Murayama, T., & Nishikizawa, S. (2019). A qualitative content analysis of environmental impact assessment in Indonesia: A case study of nickel smelter processing. *Impact Assessment and Project Appraisal, 38*(3), 194–204. https://doi.org/10.1080/14615517.2019.1672452

Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2016). Machine learning in geosciences and remote sensing. *Geoscience Frontiers, 7*(1), 3–10. https://doi.org/10.1016/j.gsf.2015.07.003

Lin, S., Liang, Z., Guo, H., Hu, Q., Cao, X., & Zheng, H. (2025). Application of machine learning in early warning system of geotechnical disaster: A systematic and comprehensive review. *Artificial Intelligence Review*, *58*(6). https://doi.org/10.1007/s10462-025-11175-0

Lundberg, S., & Lee, S.-I. (2017, May 22). *A unified approach to interpreting model predictions*. arXiv.Org. https://arxiv.org/abs/1705.07874

Mathys, A. S., van Vianen, J., Rowland, D., Narulita, S., Palomo, I., Pascual, U., Sutherland, I. J., Ahammad, R., & Sunderland, T. (2023). Participatory mapping of ecosystem services across a gradient of agricultural intensification in West Kalimantan, Indonesia. *Ecosystems and People, 19*(1). https://doi.org/10.1080/26395916.2023.2174685

Muhammad, S., Arifin, S., Syam, R., Tamma, S., Hans, A., Hanami, Z. A., Aprianto, & Putra, B. A. (2024). Corporate social responsibility programs in mining areas: Insights from stakeholder groups in Indonesia. *Cogent Social Sciences, 10*(1). https://doi.org/10.1080/23311886.2024.2357675

Nobahar, P., Xu, C., Dowd, P., & Shirani Faradonbeh, R. (2024). Exploring digital twin systems in mining operations: A review. *Green and Smart Mining Engineering*, *1*(4), 474–492. https://doi.org/10.1016/j.gsme.2024.09.003

Olawade, D. B., Wada, O. Z., Ige, A. O., Egbewole, B. I., Olojo, A., & Oladapo, B. I. (2024). Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. *Hygiene and Environmental Health Advances*, *12*, 100114. https://doi.org/10.1016/j.heha.2024.100114

Sanchez, T. W., Brenman, M., & Ye, X. (2024). The ethical concerns of artificial intelligence in urban planning. *Journal of the American Planning Association, 91*(2), 294–307. https://doi.org/10.1080/01944363.2024.2355305

Scalambrin, L., Zanella, A., & Vilajosana, X. (2023). LoRa multi-hop networks for monitoring underground mining environments. *2023 IEEE Globecom Workshops (GC Wkshps)*, 696–701. https://doi.org/10.1109/gcwkshps58843.2023.10464954

Singh, M., & Yan, S. (2021). Spatial–temporal variations in deforestation hotspots in Sumatra and Kalimantan from 2001–2018. *Ecology and Evolution, 11*(12), 7302–7314. https://doi.org/10.1002/ece3.7562

Tost, M., Hitch, M., Chandurkar, V., Moser, P., & Feiel, S. (2018). The state of environmental sustainability considerations in mining. *Journal of Cleaner Production*, *182*, 969–977. https://doi.org/10.1016/j.jclepro.2018.02.051

United Nations. (2015). *THE 17 GOALS*. Sustainable Development. https://sdgs.un.org/goals

Viet Du, Q. V., Nguyen, H. D., Pham, V. T., Nguyen, C. H., Nguyen, Q.-H., Bui, Q.-T., Doan, T. T., Tran, A. T., & Petrisor, A.-I. (2023). Deep learning to assess the effects of land use/land cover and climate change on landslide susceptibility in the Tra Khuc river basin of Vietnam. *Geocarto International, 38*(1). https://doi.org/10.1080/10106049.2023.2172218

Wahyono, Y., Sasongko, N. A., Trench, A., Anda, M., Hadiyanto, H., Aisyah, N., Anisah, A., Ariyanto, N., Kumalasari, I., Putri, V. Z. E., Lestari, M. C., Panggabean, L. P., Ridlo, R., Sundari, S., Suryaningtyas, A. D., Novianti, E. D., Hakim, M. R. F., Prihatin, A. L., & Matin, H. H. A. (2024). Evaluating the impacts of environmental and human health of the critical minerals mining and processing industries in Indonesia using life cycle assessment. *Case Studies in Chemical and Environmental Engineering*, *10*, 100944. https://doi.org/10.1016/j.cscee.2024.100944

Yadav, S., Samadhiya, A., Kumar, A., Luthra, S., & Pandey, K. K. (2024). Environmental, social, and governance (ESG) reporting and missing (M) scores in the industry 5.0 era: Broadening firms' and investors' decisions to achieve sustainable development goals. *Sustainable Development, 33*(3), 3455–3477. https://doi.org/10.1002/sd.3306

Zhan, S., Huang, L., Luo, G., Zheng, S., Gao, Z., & Chao, H.-C. (2025). A review on federated learning architectures for privacy-preserving AI: Lightweight and secure cloud–edge–end collaboration. *Electronics*, *14*(13), 2512. https://doi.org/10.3390/electronics14132512

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