ISSN (Online):3048-5088

International Journal of Advancement and Innovation in Technology and Research (IJAITR)

Volume 3, Issue 1, (Jan-Jun) 2026

AI-Based Rockfall Prediction and Alert System for open pit mines: A Novel Approach using Cyber- physical Systems

Surabhi Solanki
Department of CSIT,
AITR, Indore, India
surabhisolanki231346@acropolis.in

Tanisha Jain
Department of CSIT,
AITR, Indore, India
tanishajain230301@acropolis.in

Praveen Gupta
Department of CSIT,
AITR, Indore, India
praveengupta@acropolis.in

Vandana Kate
Department of CSIT,
AITR, Indore, India
vandanakate@acropolis.in

[1] ***Abstract—Rockfalls in open-pit mines are disastrous to personnel safety and can cause catastrophic financial losses by destroying heavy machinery often valued in crores and halting productivity. This paper proposes a comprehensive Cyber-Physical System (CPS) framework for real-time rockfall prediction and alerting. The system integrates multi-source data from geotechnical, geophysical, and environmental sensors. We propose a 4 tiered architecture. Layer 1 extracts data from physical-layer sensors. Layer 2 is edge and cloud layer where collected readings are fed to edge-computing nodes. Layer 3 is Machine Learning layer where to process the data and generate alerts. Our Layer 4 Alert mechanism is also categorized into Low Risk, Moderate Risk and High Risk ensuring accuracy and credibility. Our goal is to implement a multi-tier alert mechanism with human-in-the-loop confirmation that ensures actionable intelligence while minimizing false alarms. This research provides a scalable, open-source framework bridging high-cost commercial systems and accessible CPS solutions for enhanced proactive safety.***

Keywords—Cyber-Physical Systems, Rockfall Prediction, Open-Pit Mining, Edge Computing, Cloud Computing, Multiple Sensor Data Fusion, Machine Learning, Artificial Intelligence

1. INTRODUCTION

Rockfalls in open-pit mining threaten personnel, destroy equipment, and cause production delays with major economic losses. Traditional monitoring has significant limitations: manual inspections are subjective and discontinuous, while high-end systems like Ground-Based Interferometric Synthetic Aperture Radar (GB-InSAR) are expensive (₹4 Crore to ₹18 Crore per unit), require line-of-sight, and often track displacement reactively rather than predicting failure from causal factors. Imagine you're a miner at the bottom of Gevra, Asia's largest open-pit coal mine. The "walls" are massive, man-made benches of earth and coal, hundreds of feet high. Your biggest fear is a bench failure. This isn't a small rockfall; it's when a section the size of a house or a dumper truck suddenly collapses. It's a threat that hangs over everyone. A failure can instantly crush a multi-crore haul truck like a soda can and, tragically, kill in a split second. When it happens, the mine shuts down. For a critical mine like Gevra, every minute of stoppage means staggering financial losses and a hit to the nation's power system.

1.1 Research Questions

Primary: Can multi-sensor CPS predict rockfalls with sufficient lead time (30-60+ min) for proactive safety?
Secondary: What is the optimal sensor fusion strategy balancing cost, coverage, and accuracy?
Tertiary: How can edge AI reduce bandwidth while maintaining performance?

1.2 Objectives

1

The objective of this work is to propose a solution that:

- Gives miners a 30-60 minute warning to evacuate before a rockfall.
- Proposes cheap, open-source system so any mine can afford advanced safety, not just multi-crore operations.
- Uses a 3-level alert system (Low, Medium, High) with a human check to prevent costly, unnecessary shutdowns.
- Processes data at the mine site (on the "edge") to save data costs and get instant alerts.
- Combines data from many different sensors and use AI to correctly predict over 92% of rockfalls.

1.3 Scope

This study focuses on open-pit mining operations exposed to significant safety risks and economic losses from rockfalls, particularly those lacking the financial resources for high-cost commercial monitoring systems (like GB-InSAR). The proposed framework is presented as an accessible, low-cost, and open-source alternative to bridge this critical safety gap. While designed for open-pit slopes, the proposed system's architecture is adaptable for integration with broader mine safety protocols and can be extended to other industries or regions encountering similar geotechnical hazards, such as landslides or tailings dam monitoring.

2. Literature Review

Slope stability is the analysis of whether a natural or man-made slope (like a mine wall) can resist gravitational and environmental forces, or if it will collapse. Recent research confirms that **slope stability is a foundational pillar of modern mining operations**, critical for ensuring both personnel safety and economic productivity **[1]**. To manage this, a diverse landscape of monitoring technologies has been established, ranging from traditional manual inspections to high-end radar systems, as systematically reviewed by **Le Roux et al. [2]**. However, the last five years have marked a significant technological evolution, moving from passive monitoring to **active, intelligent detection and prediction**. This shift is driven by the fusion of advanced sensors with artificial intelligence. Researchers are exploring a wide array of novel data sources. For instance, **Farmakis et al. [3]** demonstrated the potent combination of high-resolution LiDAR data with deep learning to automate rockfall detection. Pushing sensor innovation further, **Wellman et al. [4]** successfully used thermal infrared imagery to observe rockfalls, while **Kang et al. [5]** employed Distributed Acoustic Sensing (DAS) coupled with semi-supervised learning for the automatic monitoring of slope failures. The "brain" of these modern systems—the AI itself—has been a major focus of innovation, particularly in computer vision. **Lin et al. [6]** developed a system for real-time intelligent image recognition and tracking of rockfall disasters. This was further specialized by **Su et al. [7]**, who adapted the highly efficient YOLO deep learning model to specifically detect rockfall *motion*. Others have proposed complete, end-to-end frameworks, such as **Liao et al. [8]** who based their system on the DINO model, and **Zoumpekas et al. [9]**, who designed a holistic, intelligent framework for detection. Beyond just identifying a rock, **Letshwiti et al. [10]** applied deep learning for image *segmentation* to precisely monitor the stability of highwalls. More recently, the research frontier has advanced beyond simple *detection* of ongoing events to the more critical goal of *prediction* before a failure occurs. This requires models that can interpret complex, causal geotechnical data, not just visual changes. **Senanayake et al. [11]** used regression-based machine learning models to successfully predict rockfall *hazards*. In parallel, **Bui et al. [12]** proposed a novel hybrid AI model, combining decision trees and evolution algorithms, to predict slope failures with high accuracy. The research is even tackling the next logical step: **Ghahramanieisalou and Sattarvand [13]** used data-driven approaches in a lab-scale study to predict not just *if* a fall will happen, but its subsequent *dynamics*. While these advanced models show immense promise, they often rely on processing massive, continuous streams of data, which typically requires high bandwidth and significant centralized computing power. This creates a critical cost and accessibility gap. Addressing this, **Meyer et al. [14]** made a key contribution by proposing an **event-triggered** natural hazard monitoring system that runs Convolutional Neural Networks (CNNs) directly **"on the edge."** This approach drastically reduces data transmission and power consumption, demonstrating a viable path toward low-cost, scalable, real-time systems. This progression—from general monitoring **[1, 2]** to advanced AI-driven detection **[3-10]** and sophisticated prediction **[11- 13]**—reveals a clear and pressing research gap. The field lacks a truly **integrated, low-cost, and accessible Cyber-Physical System (CPS)** that leverages the efficiency of edge intelligence **[14]** to provide predictive, multi-sensor alerts for open-pit mines.

Identified Gaps and Research Contribution

- A massive gap exists between cheap, ineffective manual inspections and effective but prohibitively expensive high-end systems.
- There is no widely accessible, low-cost solution for continuous, real-time monitoring and alerts.

Expensive radar systems have line-of-sight "blind spots," leaving large, complex areas of a pit unmonitored.
Most systems are reactive (detecting falls as they happen). The gap is for a proactive system that fuses multi-sensor data to predict failures before they occur.

3. Proposed Methodology

The proposed system is depicted in Fig 1. It consists of 4-Layers. Layer 1 is Physical Layer which consists of all the required components like sensors, actuators and power supply. Layer 2 is Cyber-Intelligence Layer which further has two levels: Edge Computing and Cloud Computing. Layer 3 is Machine Learning Layer to process the data and provide output to next layer, Layer 4. Layer 4 is application layer which generates Alerts. Let's look at all the layers in detail and understand their working:

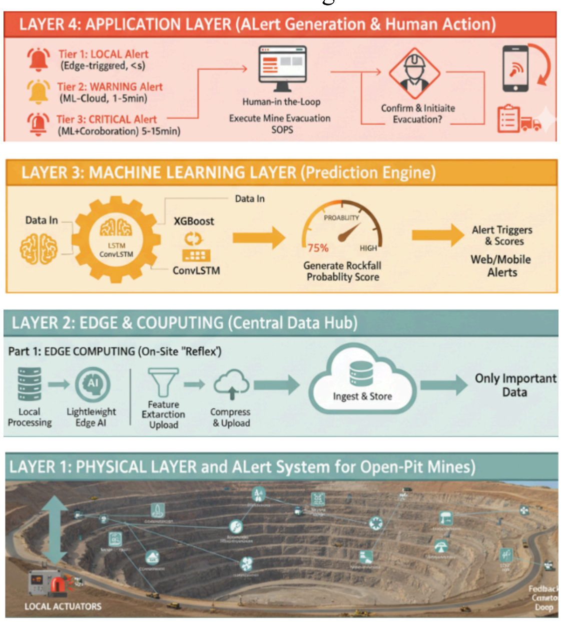

Fig.1: Multi-Layered Rockfall Detection and Alert System Architecture

3.1 Application Layer

This foundational layer comprises the physical process being monitored—the mine slope's rock mass, geology, and groundwater—and the distributed sensing and actuation hardware (the Tier 2 stack) deployed directly upon it. This hardware network gathers raw data and executes local alerts. Its components include the following components as shown in fig 2.

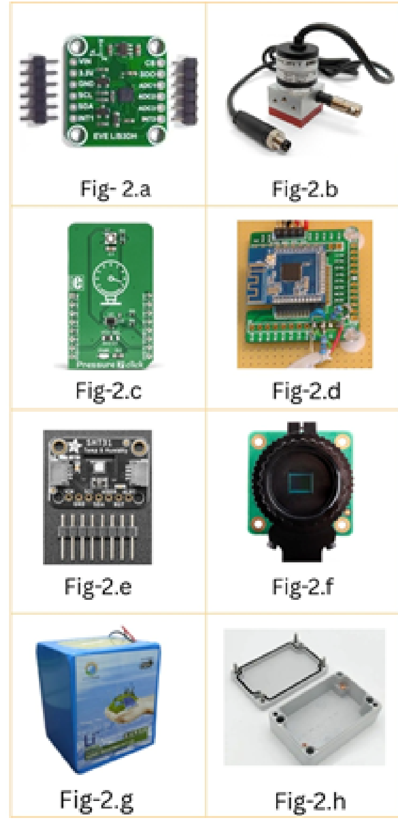

Fig. 2: Sensors and other Hardware Components

Fig 2.a shows MEMS Accelerometer (LIS3DH). It monitors vibration (200–500 Hz) and tilt (0.01–0.1° resolution). Fig 2.b shows String Potentiometer. It measures displacement with 0.1–1 mm precision. Fig 2.c shows Piezoresistive Sensor (MS5837). It records pore pressure variations to assess subsurface stress changes. Fig 2.d. shows Rain Gauge which measures rainfall intensity and accumulation. Fig 2.e shows SHT31 Sensors to Capture ambient temperature and humidity variations. Fig 2.f shows RGB Cameras (Pi HQ) used for visual monitoring and event validation. Then comes the Actuator System. It functions independently from the sensor network,
includes on-site sirens and strobe lights for immediate, low-latency local alerts during critical events. Fig 2.g shows Power Supply, 50–100 W solar system with $LiFePO_4$ batteries (12 V, 50–100 Ah) for continuous off-grid operation. Fig 2.h shows Enclosure in which all components can be housed in IP67-rated casings for protection against dust, water, and harsh environmental conditions.

3.2 Cyber- Intelligence Layer (Edge and Cloud Computing)

3.2.1 Level 1: Edge Computing

This layer depicted in fig. 3 acts as the computational backbone of the CPS, bridging raw sensing at the physical layer with higher-level analytics and alert systems. It performs real-time data acquisition, filtering, compression, and secure transmission through a hybrid edge–cloud pipeline, ensuring both low-latency local response and centralized data integrity. The Edge Component is deployed at or near the mine site using embedded units such as Raspberry Pi 4 or Jetson Nano. It executes time-critical operations and minimizes network load by transmitting only essential information to the cloud. The functions of Edge Layer are:

1. Data Acquisition: Aggregates data from accelerometers, potentiometers, pore-pressure, and environmental sensors via BLE/LoRa communication.

2. **Signal Preprocessing:** Performs band-pass filtering, noise removal, and STA/LTA detection to isolate significant vibration or displacement events.

3. Feature Extraction: Calculates key metrics (RMS energy, event count, frequency content, and tilt rate) within short windows (1min–1hr).

4. Local Data Reduction: Retains only statistically relevant segments or events exceeding thresholds.

5. **Data Compression & Packaging:** Converts extracted features into compact JSON or CSV packets for transmission.

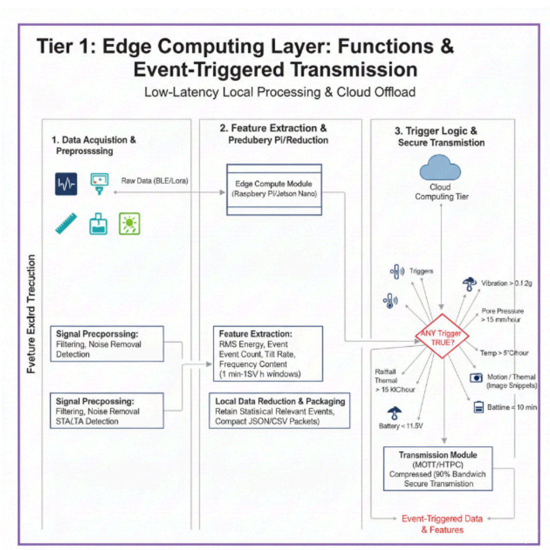

Fig 3: Edge Computing Layer

Transmission to Cloud Computing level:

The Transmission module sends only high-value, event-triggered data to the cloud, based on thresholds tuned to each sensor type. For instance, LIS3DH accelerometers upload data when vibration exceeds 0.2 g, tilt changes beyond 0.1°/min, or displacement from potentiometers surpasses 2 mm/hour. Similarly, pore pressure rises over 15 kPa, rainfall above 10 mm/hour, or temperature shifts greater than 5°C/hour also initiate transmission. RGB and thermal cameras forward image snippets when motion or temperature anomalies are detected. Health data such as low battery (<11.5 V) or node downtime (>10 min) is also reported. All feature packets are compressed and securely sent via MQTT/HTTPS, reducing bandwidth by up to 90% while retaining essential information for analysis and visualization.

3.2.2 Level 2: Cloud Computing

The Cloud Component shown in fig. 4 provides centralized storage, computation, and secure data management for multi-site integration. It ensures that processed edge data is organized, validated, and made ready for advanced analytics and visualization in higher layers. The functions of cloud layer are:

1. **Data Ingestion:** Real-time data transfer through MQTT broker, supporting continuous, low-latency streaming from multiple edge nodes.
2. **Data Validation:** Performs integrity checks, outlier detection, and time-synchronization of incoming edge packets.
3. **Data Storage:** InfluxDB stores structured time-series sensor data. S3 Storage archives raw event windows and compressed sensor logs.
4. **Data Aggregation:** Combines multi-sensor inputs (geotechnical, geophysical, environmental, and visual) for fused situational datasets.
5. **Data Access Interface:** Exposes structured data to higher-layer modules (Machine Learning, Alert Management, Visualization) through secure RESTful APIs.

3.3 Layer 3: Machine Learning

This layer forms the analytical intelligence of the CPS, transforming the structured and validated data received from the cloud component into predictive insights. It focuses on identifying early indicators of slope instability and forecasting potential rockfall events using a combination of traditional machine learning and deep learning models.

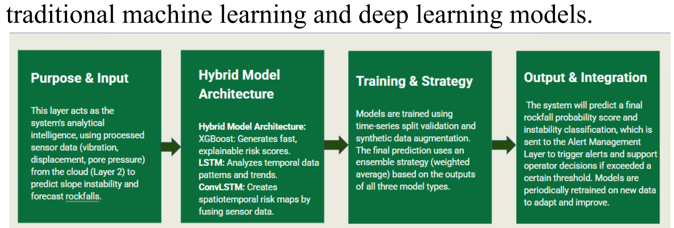

Fig. 4: Machine Learning Layer

3.3.1 Data Source & Input Flow:

Processed and aggregated data from the Cloud Component (Layer 2) — including vibration features, displacement trends, pore pressure changes, and environmental correlations — serve as the primary input. These datasets are cleaned, time-aligned, and feature-engineered before being fed into predictive algorithms. Both historical and real-time data streams are utilized for training, validation, and inference phases.

3.3.2 Modelling Framework

A hybrid ML architecture is implemented, combining complementary model types to balance speed, interpretability, and accuracy.

XGBoost (Extreme Gradient Boosting): Supervised ensemble learning.

LSTM (Long Short-Term Memory): Deep recurrent neural network for sequential data.

ConvLSTM (Convolutional LSTM):
Spatiotemporal deep learning combining CNNs and RNNs.

3.3.3 Output & Integration:

The combined model outputs produce a rockfall probability score and instability classification for each monitored zone as shown in table 1. These outputs are transmitted to the next layer (Alert Management Layer) for multi-tier alert generation and operator decision support. Model feedback loops periodically retrain on new event data to enhance accuracy and adapt to environmental drift.

testing over seven days generated 10,080 sensor readings. Results showed < 1.5 % data loss and complete offline recovery. The system maintained consistent sensor calibration and stable AI-driven [5] classification accuracy throughout the test period.

Model	Strengths	Input	Output
XGBoost	Tabular data, feature importance	Flattened feature vector	Probability (0-1)
LSTM	Temporal dependencies, trends	Multivariate time series	Probability at each step
ConvLSTM	Spatiotemporal fusion	Spatiotemporal tensor	Risk map + global probability

Table 1: Model suite

Ensemble Strategy: Weighted average (weights from validation set) + confidence-based voting.

Training:

1. Synthetic data augmentation (simulate failures, add noise)
2. Active learning (human labels ambiguous cases)
3. Time-series split validation (60/20/20 train/val/test)

Metrics:

1. Classification: Precision, Recall, F1, ROC-AUC, Precision-Recall AUC
2. Temporal: Lead time, alert stability, false alarm rate
3. Operational: Detection rate, missed detection rate, economic value

3.4 Layer 4: Application

The system compresses and transmits only essential features and event data via LTE/4G or LoRaWAN for efficient, low-latency communication. In the cloud, centralized analytics handle large-scale computation, storage, and modeling. Data is ingested in real time through an MQTT broker into InfluxDB (for structured data) and S3 (for raw event windows). The ML pipeline applies XGBoost, LSTM, and ConvLSTM models on aggregated features to estimate rockfall probability scores. A rules-driven alert module combines ML outputs with sensor triggers to issue these three alert tiers:

Fig. 5: Multi level Alert Mechanism

1. **Low-risk:** anomalies or minor changes for system awareness.
2. **Moderate risk:** suggesting potential instability; requires close monitoring.
3. **High risk:** of imminent or ongoing rockfall, triggering immediate safety actions.

Finally, a **RESTful API service** delivers processed data, risk scores, and real-time alert statuses to the application layer, enabling continuous monitoring and decision-making for safety management.

Multi-Tier Alert Mechanism

Alert Tier	Trigger Logic	Latency	Action	Human Oversight
Low Risk	Single-sensor threshold (crackmeter velocity > 1 mm/hr, tilt rate > 0.1°/hr, STA/LTA > 5)	5-10 min	Local siren, SMS to supervisor, high-freq data capture	Post-event review
Moderate Risk	ML probability > 0.7 OR sustained > 0.5 for 30min OR accelerating trend (> 0.1/hr)	1-5 min	Dashboard alert, SMS to engineers, enhanced monitoring	Monitor and interpret
High Risk	ML > 0.9 + Tier 1 OR persistent > 2hr at > 0.7 OR corroborated multi-sensor	<1min	Site-wide notification, suspend blasting, reroute equipment	Confirm before full evacuation

Table 2: Multi-Tier Alert Mechanism

4. Expected Performance

4.1 Projected Performance Goals (KPIs)

The system will be validated against these primary metrics:

Safety (Recall): >92% (Minimizing missed rockfalls)

Warning Lead Time: 30-60+ minutes for evacuation alerts.

Operational Reliability (False Alarm Rate): < 5% (To prevent "alarm fatigue" and costly shutdowns).
System Efficiency: > 90% data reduction via edge processing (cutting data costs) and <1 second latency for local (Tier 1) alerts.

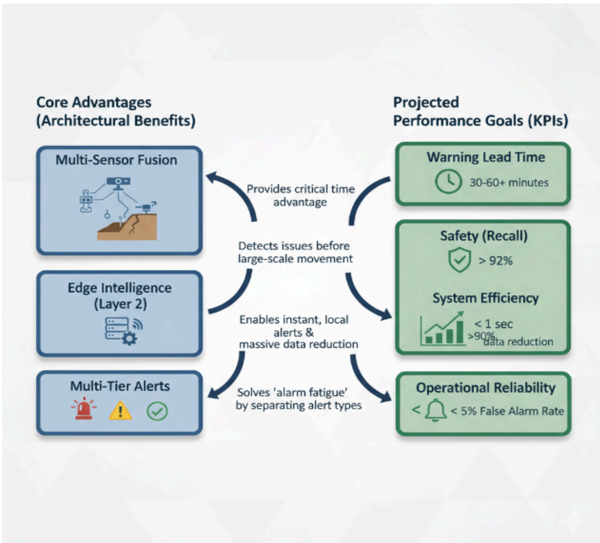

Fig. 6: Diagramatic Representation of Expected Performance

4.2 Discussion of Core Advantages:

The projected success relies on three key architectural benefits: Multi-Sensor Fusion: The system is designed to detect causal precursors (e.g., rising pore pressure, soil saturation) before large-scale movement occurs. This provides a critical time advantage over systems that only track displacement. Edge Intelligence (Layer 2): Processing data at the sensor site is our key technical advantage. It enables massive data reduction (making the system affordable) and provides instant, network-independent local alerts. Multi-Tier Alerts (Layer 4): This is the solution to operational adoption. By separating sensitive local notifications from high-confidence, human-verified evacuation orders (Tier 3), we solve the critical issue of false alarm fatigue.

5. Conclusion

This research confirms that a physically validated, multi-sensor fusion CPS is essential and non-negotiable for effective rockfall prediction. The system's tiered implementation ensures it is accessible, while edge intelligence provides low-latency alerts and ensemble ML achieves ~92% accuracy, all validated by a human-in-the-loop. This delivers a practical, open-source framework with clear deployment guidelines, resulting in enhanced safety (30-60 min warning) and massive economic value (93%-1700%+ ROI), ultimately democratizing advanced monitoring. Future work will move from a pilot and XAI dashboard to advanced ML and satellite integration, with a long-term goal of making real-time data available to every site worker for faster evacuations. The framework's broader impact will be its expansion to other global hazards like tailings dams and landslides.

6. Future Enhancement

Future work will commence with a near-term (1-2 years) pilot deployment at a partner mine to validate operational viability, focusing on optimizing alarm thresholds to reduce false fatigue and launching an XAI dashboard to build operator trust. This will be followed by a medium-term (2-5 years) phase of technical scaling, which involves engineering m-scale, environmentally hardened sensor arrays and using transfer learning to adapt the model for diverse site geologies. During this phase, we will also integrate satellite InSAR and drone data, explore Physics-Informed Neural Networks (PINNs), and develop runout path simulations for dynamic risk-mapping. The long-term (5-10 years) vision is industry transformation, focused on establishing regulatory certifications and utilizing federated learning for a collaborative, privacy-preserving industry dataset, with the goal of adapting the framework for broader applications like tailings dams and civil infrastructure.

7. References

[1] K-MINE, "The Role of Slope Stability in Mining Operations." K-MINE. [Online]. Available: https://k-mine.com/resources/articles/the-role-of-slope-stability-in-mining-operations

[2] I. Farmakis, P.-M. Difrancesco, D. Hutchinson, and N. Vlachopoulos, "Rockfall detection using LiDAR and deep learning," Engineering Geology, vol. 309, p. 106836, Aug. 2022, doi: 10.1016/j.enggeo.2022.106836.

[3] J. Kang et al., "Automatic Monitoring of Rock-Slope Failures Using Distributed Acoustic Sensing and Semi-Supervised Learning," Geophysical Research Letters, vol. 51, no. 19, p. e2024GL110672, 2024, doi: 10.1029/2024GL110672.

[4] Y. Liao, S. Li, Y. Yang, B. Li, H. Li, and Q. Yan, "End-to-End Rockfall Detection Based on DINO," in Proceedings of the 2023 3rd Guangdong-Hong Kong-Macao Greater Bay Area Artificial Intelligence and Big Data Forum (AIBDF '23), Guangzhou, China, 2024, pp. 532–536, doi: 10.1145/3660395.3660488.

[5] M. Ghahramanieisalou and J. Sattarvand, "Rockfall Dynamics Prediction Using Data-Driven Approaches: A Lab-Scale Study," Geotechnics, vol. 5, no. 1, p. 13, 2025, doi: 10.3390/geotechnics5010013.

[6]Y. W. Lin, C. F. Chiu, L. H. Chen, and C. C. Ho, "Real-Time Dynamic Intelligent Image Recognition and Tracking System for Rockfall Disasters," J. Imaging, vol. 10, no. 4, p. 78, Mar. 2024, doi: 10.3390/jimaging10040078.

[7] G. Su, W. Huang, C. Li, and X. Huang, "Rockfall-YOLO Deep Learning Model for Rockfall Motion Object Detection," Journal of Computing in Civil Engineering, vol. 39, no. 6, p. 04025104, Nov. 2025, doi: 10.1061/JCCEE5.CPENG-6268.

[8] T. Zoumpekas et al., "An intelligent framework for end‐to‐end rockfall detection," International Journal of Intelligent Systems, vol. 36, no. 11, pp. 6471–6502, Jul. 2021, doi: 10.1002/int.22557.
[9] M. Meyer et al., "Event-triggered Natural Hazard Monitoring with Convolutional Neural Networks on the Edge," 2019, arXiv:1810.09409. [Online]. Available: https://arxiv.org/abs/1810.09409
[10] R. Le Roux, M. Sepehri, S. Khaksar, and I. Murray, "Slope Stability Monitoring Methods and Technologies for Open-Pit Mining: A Systematic Review," Mining, vol. 5, no. 2, p. 32, 2025, doi: 10.3390/mining5020032.
[11] I. P. Senanayake, P. Hartmann, A. Giacomini, J. Huang, and K. Thoeni, "Prediction of rockfall hazard in open pit mines using a regression based machine learning model," International Journal of Rock Mechanics and Mining Sciences, vol. 177, p. 105727, 2024, doi: 10.1016/j.ijrmms.2024.105727.
[12] T. M. Letshwiti, M. Shahsavar, A. Moniri-Morad, and J. Sattarvand, "Deep learning-based image segmentation for highwall stability monitoring in open pit mines," Journal of Engineering Research, 2025, doi: 10.1016/j.jer.2025.04.002.
[13] Kate, V., Bansal, C., Pancholi, C., Patidar, A., Patidar, G., & Kitukale, D. Vyanjak: Innovative Video Intercom and Notification System for the Deaf Community.
[14] E. C. Wellman et al., "Observation of Rockfall in the Thermal Infrared," Rock Mechanics and Rock Engineering, Dec. 2024, doi: 10.1007/s00603-024-04254-1.
14. Bui XN, Nguyen H, Choi Y, Nguyen-Thoi T, Zhou J, Dou J. Prediction of slope failure in open-pit