

AI-Based Rockfall Prediction and Alert System for Open-Pit Mines

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Abstract - Rockfalls threaten personnel and production in open-pit mines, yet radar-based monitoring is too costly for many small and public-sector operations. This paper proposes the Rockfall Prediction and Alert System (RPAS), an artificial intelligence framework that fuses digital elevation models, drone imagery, geotechnical sensor readings, and environmental data into a Probability-of-Failure (PoF) score for each slope sector. The design combines a convolutional branch for imagery and terrain, a recurrent (LSTM) branch for sensor trends, and a tree-ensemble branch for tabular risk factors, joined by a stacking meta-learner. Scores feed a risk-map dashboard and a four-tier SMS and email alert workflow running on low-cost, open hardware. Expected performance is framed against published benchmarks, and a phased field-validation plan is described.

Keywords: Rockfall prediction; Machine learning; Sensor fusion; Early warning system

INTRODUCTION

Open-pit mines expose tall, steep rock faces to weathering, blast vibration, rainfall infiltration, and stress redistribution, which erode slope stability and can end in sudden rockfalls or larger failures. Such events endanger workers, interrupt production, and bring regulatory and legal consequences, and evidence from large open-pit operations shows that slope instability is a recurring hazard rather than a rare event (Wang et al., 2023).

Slope stability has traditionally been judged with limit-equilibrium and numerical methods that return a deterministic factor of safety from idealized assumptions. These methods struggle to represent the non-linear, spatially varied, and time-dependent behavior of real rock masses, especially under heavy rain or repeated blasting ("Prediction of Slope Stability," 2025). Field instruments and slope radar give direct evidence of movement, but proprietary radar is costly to buy and maintain, which places it beyond many public-sector and small private mines. Affordable open hardware paired with machine learning is therefore needed.

LITERATURE REVIEW

Recent studies have applied machine learning directly to slope stability. Wang et al. (2023) used a deep-learning model to predict the stability coefficient of an open-pit slope under rainfall and reported estimates that followed measured displacement more closely than conventional calculations. Mahmoodzadeh et al. (2023) compared twelve machine-learning techniques for estimating the safety factor of 344 open-pit rock slopes. For

classifying slope status, a random forest tuned with a genetic algorithm reached 93% accuracy, against 86% for a similarly tuned support vector machine (“Prediction of Slope Stability,” 2025).

Work on unmanned aerial vehicle (UAV) photogrammetry points the same way. Yousefi et al. (2019) showed that UAV point clouds can reveal probable rockfall zones without contact instruments, and a systematic review by Tangadzani et al. (2024) found that most studies still treat imagery as a stand-alone survey product, even though repeat surveys can resolve bench-scale movement at a fraction of the cost of laser scanning or radar (Pashchenko et al., 2025). On the sensing side, Abraham et al. (2020) built an IoT network of MEMS tilt and soil-moisture sensors in the Darjeeling Himalayas and showed that physical sensing lowers the false-alarm rate of rainfall-threshold landslide warnings, a threshold approach rooted in the work of Baum and Godt (2010).

RESEARCH GAP

Single-modality focus. Machine-learning studies on open-pit slopes mostly use tabular geotechnical and geometric features, UAV studies mostly treat imagery as a stand-alone survey, and IoT studies focus on rainfall-triggered landslides. Few studies combine terrain features from a digital elevation model (DEM), drone-imagery change detection, geotechnical time series, and environmental data in one prediction pipeline for open-pit mines.

Cost and scalability. Radar-based early-warning systems work but are too costly for many public-sector and small private mines. Few studies pair prediction with low-cost open hardware that can be extended across sites.

Data and decision support. Labeled rockfall datasets for open-pit mines are scarce, which limits validation, and few pipelines link model output to tiered, explainable alerts that mine planners can act on.

PROBLEM STATEMENT

Open-pit mines need an affordable, AI-based system that predicts rockfall before it happens. As Problem Statement 25071, issued by the Ministry of Mines through the National Institute of Rock Mechanics (NIRM, n.d.), requires, the system must combine DEM, drone imagery, geotechnical sensor data, and environmental data; show real-time risk maps and probability-based forecasts on a planner-friendly dashboard; and send SMS or email alerts with suggested actions. Current practice relies on manual inspection or costly radar, which leaves many mines without continuous monitoring.

PROPOSED SYSTEM

This paper proposes RPAS, which fuses the four data sources into one PoF score per slope sector. Its contributions are (a) a layered architecture that builds a spatially indexed risk model from the four sources, (b) a hybrid three-branch machine-learning pipeline that

yields an interpretable PoF score and risk tier, (c) a dashboard and tiered alert workflow that turns model output into role-specific action, and (d) a low-cost, open-hardware plan with an evaluation strategy.

SYSTEM ARCHITECTURE

RPAS is organized into six layers: acquisition, preprocessing, machine-learning inference, risk mapping, alerting, and a dashboard. Figure 1 shows how data move through the main stages.

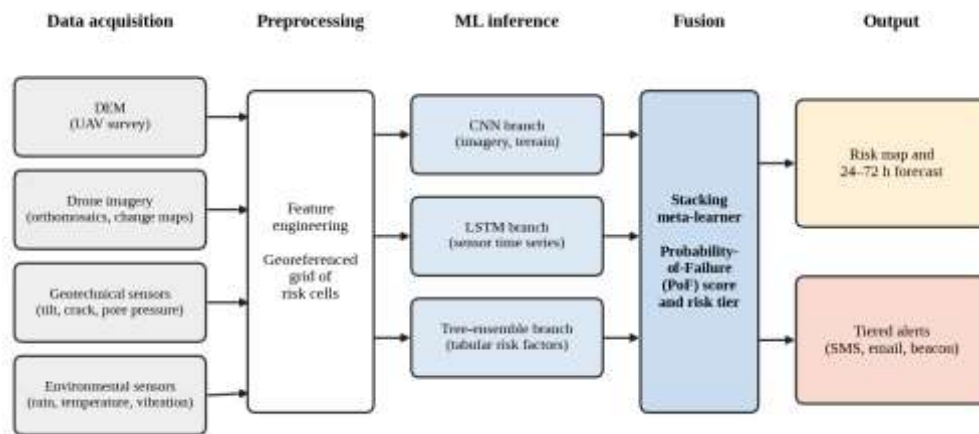


Figure 1 Layered Data Flow of the Rockfall Prediction and Alert System (RPAS)

Note. DEM = digital elevation model; CNN = convolutional neural network; LSTM = long short-term memory; PoF = Probability-of-Failure.

A DEM is generated from UAV LiDAR or photogrammetric surveys at centimeter-scale resolution and used to derive slope angle, aspect, curvature, bench geometry, and deviation from the planned design. Drone imagery, captured on a periodic schedule, is processed into orthomosaics, and successive surveys are different to detect surface change. Geotechnical sensors (MEMS tilt sensors, crack-meters, and vibrating-wire piezometers) are placed on benches that the DEM and imagery analysis rank as higher risk, and environmental sensors (a rain gauge, a temperature and humidity probe, and a geophone for blast vibration) complete the field suite. Nodes send data over a LoRaWAN or NB-IoT mesh to a solar-powered edge gateway, which forwards it to a server when connectivity allows.

METHODOLOGY / WORKFLOW

Preprocessing resamples all time series to a common interval, fills gaps, and computes displacement rate, displacement acceleration (a widely used precursor signal), and 1-, 3-, 7-, and 30-day cumulative rainfall. The pit surface is divided into a georeferenced grid of risk cells, and every derived feature is aligned in space and time to its cell.

Inference uses three complementary branches (Table 1). A lightweight convolutional network scans orthoimagery and DEM-derived hillshade and curvature maps for cracks,

loose blocks, and rockfall scars. A long short-term memory (LSTM) network processes multivariate sensor sequences, because recurrent models of this kind capture the long-range dependencies typical of slowly developing failure precursors (Hochreiter & Schmidhuber, 1997). A random-forest or gradient-boosted ensemble handles static and slowly varying features and stays robust on limited or synthetic data (Breiman, 2001). A stacking meta-learner merges the branch outputs into one PoF score per risk cell per time step, mapped to four tiers: Low, Medium, High, and Critical.

Table 1 Machine-Learning Components of RPAS

Branch	Primary input	Model	Purpose
Imagery/terrain	Orthomosaic, DEM hillshade and curvature	Lightweight CNN	Detects cracks, loose blocks, and surface change
Temporal	Displacement, pore pressure, vibration, and rainfall series	LSTM	Detects precursor trends
Tabular	Slope geometry, discontinuity indices, rainfall, failure history	Random forest / gradient boosting	Gives baseline probability from static features
Fusion	Outputs of all branches	Stacking meta-learner	Produces PoF score and risk tier

PoF scores are drawn as a color-coded heat map over the DEM and orthomosaic and refreshed as data arrive. A 24–72 hour forecast extrapolates the LSTM displacement-rate trend and adds forecast rainfall from an external weather service, and an inverse-velocity-style extrapolation gives an indicative time to failure when displacement acceleration passes a calibrated threshold, as a planning horizon rather than a precise prediction.

MATHEMATICAL FORMULATION

For risk cell c at time t , the three branches return the probabilities p_{CNN} , p_{LSTM} and p_{ENS} . The stacking meta-learner combines them into the PoF score, where σ is the logistic function and the weights w_0 to w_3 are learned on held-out branch predictions:

$$\text{PoF}(c, t) = \sigma(w_0 + w_1 p_{\text{CNN}} + w_2 p_{\text{LSTM}} + w_3 p_{\text{ENS}}) \quad (1)$$

The risk tier follows from calibrated thresholds $\tau_1 < \tau_2 < \tau_3$:

$$\text{Tier} = \text{Low if } \text{PoF} < \tau_1; \text{ Medium if } \tau_1 \leq \text{PoF} < \tau_2; \quad (2)$$

$$\text{High if } \tau_2 \leq \text{PoF} < \tau_3; \text{ Critical if } \text{PoF} \geq \tau_3$$

The displacement rate, displacement acceleration and cumulative rainfall features are computed as follows, where $d(t)$ is the cumulative displacement, $r(s)$ is the rainfall intensity and T takes the values 1, 3, 7 and 30 days:

$$v(t) = [d(t) - d(t - \Delta t)] / \Delta t \quad (3)$$

$$a(t) = [v(t) - v(t - \Delta t)] / \Delta t \quad (4)$$

$$R_T(t) = \int r(s) ds, \text{ integrated from } t - T \text{ to } t \quad (5)$$

When the acceleration passes the calibrated threshold, the indicative time to failure t_f is obtained by fitting a straight line to the inverse velocity and extrapolating to the point where it reaches zero:

$$1 / v(t) \approx mt + c, \quad t_f = -c / m \quad (m < 0) \quad (6)$$

Because a missed rockfall costs far more than a false alarm, recall is weighted above precision using the F-beta score with $\beta > 1$ (for example, $\beta = 2$). Alert lead time and false alarms per monitoring month complete the evaluation measures, where t_{event} is the time of the rockfall and t_{alert} is the time of the first alert:

$$F_\beta = (1 + \beta^2) \times \text{Precision} \times \text{Recall} / (\beta^2 \times \text{Precision} + \text{Recall}) \quad (7)$$

$$\text{Lead time} = t_{\text{event}} - t_{\text{alert}} \quad (8)$$

IMPLEMENTATION & TESTING

Alerts combine hard limits (for example, pore pressure or displacement rate above a calibrated value) with the PoF tier and follow the four levels in Table 2, each with an action-plan template. De-duplication and escalation rules limit alarm fatigue, and an Evacuate alert needs confirmation from a duty geotechnical engineer before site-wide broadcast. The dashboard offers role-based views for planners, geotechnical engineers, and field crews, and an explainability panel lists the top contributing features behind each alert.

Table 2 Alert Tiers and Recommended Actions

Tier	Trigger	Channel	Recommended action
Advisory	PoF in Low–Medium band, rising trend	Dashboard	Note sector; no operational change
Watch	PoF in Medium band, sustained	Dashboard, email	Increase monitoring frequency
Warning	PoF in High band or threshold breach	SMS, email, dashboard	Restrict equipment access; inspect
Evacuate	PoF in Critical band, human-confirmed	SMS, email, on-site beacon	Halt operations; evacuate sector

Each field node pairs an ESP32-class microcontroller with a MEMS tilt sensor, a crack-meter, and, where budget allows, a vibrating-wire piezometer, plus a geophone and rain gauge. Nodes relay over LoRa to a solar-powered Raspberry Pi-class gateway that runs quantized versions of the ensemble and LSTM models, so basic anomaly flags keep working during backhaul outages. Sensors are concentrated on the benches ranked most susceptible by the DEM analysis, while lower-risk sectors rely mainly on periodic imagery. The software stack is open source (TensorFlow Lite, MQTT, PostgreSQL with PostGIS, and Leaflet).

Component costs run from about USD 5–15 for a tilt sensor to USD 80–200 for a piezometer, with other parts roughly USD 10–80 each (order-of-magnitude estimates), so a complete node should cost a small fraction of one proprietary slope radar unit (Abraham et al., 2020).

Labeled rockfall datasets are scarce, so three strategies are combined: physics-informed synthetic data from limit-equilibrium and numerical models run over perturbed geometry, strength, and rainfall parameters; transfer learning from published case-study data; and active learning, in which field-confirmed outcomes retrain the fusion layer. Evaluation uses precision, recall, F1-score, and AUC-ROC, with recall weighted above precision because a missed rockfall costs far more than a false alarm, alongside alert lead time and false alarms per monitoring month. Site-wise k-fold cross-validation, which tests on held-out sites, estimates how the model generalizes to a new mine. Indicative targets are recall and precision of at least 0.80 and 0.70 for Medium, 0.90 and 0.75 for High, and 0.95 and 0.80 for Critical.

RESULT

Because this is a hackathon-stage proposal, full field validation lies beyond the current scope, and performance is framed against published benchmarks. Genetic-algorithm-tuned random forest and support vector machine classifiers have reached 93% and 86% accuracy on open-pit slope status (“Prediction of Slope Stability,” 2025), and deep-learning stability estimates have followed instrumented displacement more closely than conventional calculation (Wang et al., 2023). These figures come from different mines and feature sets, so they are plausibility benchmarks for the individual techniques, not a guarantee for the fused system. Site-wise cross-validation and a shadow-mode pilot are meant to give a site-verified estimate before the system informs operational decisions.

Suppose a bench sector shows several days of rising pore pressure, accelerating crack-meter displacement, and a forecast of heavy rain within 48 hours. No single signal may cross a fixed threshold, but the fusion layer, having learned the joint pattern, raises the cell to the High tier and issues a Warning, mirroring the reported benefit of combining physical sensing with rainfall thresholds (Abraham et al., 2020). Failure regimes differ: slow, rainfall-driven failures give the temporal branch ample signal, whereas sudden wedge or toppling failures may show little precursor movement, so a newly opened crack found in a UAV survey becomes the main early warning. This is why the three branches are complementary rather than redundant.

Table 3 Qualitative Comparison of RPAS with Conventional Monitoring Approaches

Approach	Coverage	Update frequency	Relative cost
Manual visual inspection	Line of sight only	Periodic (days)	Low
Proprietary slope radar	Wide area, sub-millimeter precision	Near-continuous	Very high
Point geotechnical sensors only	Single points	Continuous	Medium
Proposed RPAS (fused)	Sensor points plus UAV-wide imagery	Continuous sensors, periodic imagery	Low–medium

Table 3 positions RPAS qualitatively; head-to-head field trials are left to future work. The aim is to bring continuous, model-assisted monitoring within reach of sites that rely on manual inspection alone, not to out-measure a dedicated radar. Three limitations apply: early model confidence rests on synthetic and transferred data until a pilot site validates it; drone surveys are less frequent than sensor readings, so a fast failure could slip between them; and LoRa bandwidth and range limits must be considered when placing nodes in deep pits.

CONCLUSION

This paper proposed RPAS, an AI-based rockfall prediction and alert system that fuses DEM, drone imagery, geotechnical sensor data, and environmental data through a hybrid CNN–LSTM–ensemble model. The resulting PoF score drives real-time risk maps, short-term forecasts, and tiered SMS and email alerts with recommended actions, all on low-cost, open hardware and software, which meets the functional requirements of Problem Statement 25071 while prioritizing affordability and scalability.

A phased rollout is envisaged: a shadow-mode pilot on one high-risk sector, promotion to operational alerting once false-alarm and missed-event rates meet the target metrics (with human sign-off for Evacuate alerts), and then extension to more sectors and mines. Future work includes field piloting, satellite InSAR for regional deformation context, federated learning across mines, and a digital-twin tool for blast-planning analysis.

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