A Zone-Aware LSTM Framework for Real-Time Rockfall Risk Prediction and Alerting in Open-Pit Mines

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***Abstract*—Rockfall incidents in open-pit mines pose a significant threat to human safety, heavy machinery, and uninterrupted mining operations. Conventional monitoring systems rely primarily on threshold-based analysis of individual geotechnical indicators, which are reactive in nature and often fail to capture gradual temporal precursors to slope instability. This paper presents a complete AI-based rockfall prediction and alert system that integrates realistic synthetic data generation, deep temporal modeling, professional risk scoring, and real-time visualization. A physics-informed mean-reverting synthetic dataset comprising 50,000 samples is designed to emulate heterogeneous zone-level behaviors observed in real mines, comprising features such as strain, pore pressure, and precipitation. A Long Short-Term Memory (LSTM) network is trained on multivariate sliding windows to predict a continuous rockfall risk index. Beyond prediction, a trend-aware alert framework is proposed, incorporating rolling risk aggregation, zone-specific baseline deviation, and persistence-based alert validation to minimize false alarms. Comparative evaluation against Linear Regression and Random Forest baselines demonstrates the superiority of the proposed approach, achieving a test MAE of 0.019 and RMSE of 0.024. The system is deployed through an interactive Gradio-based dashboard enabling real-time zone-wise monitoring and decision support. The results confirm the robustness, interpretability, and deployment readiness of the proposed framework for intelligent mine safety systems.**

***Index Terms*—Rockfall Prediction, Open-Pit Mining, LSTM, Time-Series Modeling, Synthetic Data, Risk Assessment, Early Warning Systems**

I. Introduction

Rockfall and slope failure incidents remain one of the most persistent and hazardous challenges in surface and open-pit mining operations worldwide. As mining activities progressively expand to greater depths and steeper slopes to meet increasing mineral demand, the likelihood of slope instability and sudden rockfall events increases significantly. Such failures result not only in substantial economic losses due to equipment damage and operational downtime but also pose severe risks to human life. Global mining safety studies and incident analyses have consistently identified slope instability as a leading cause of fatal accidents in open-pit mines, underscoring the need for reliable early-warning and monitoring systems [1], [2].

Traditional rockfall monitoring approaches primarily rely on geotechnical instrumentation such as extensometers, inclinometers, piezometers, and micro-seismic sensors, often supplemented by periodic visual inspections conducted by domain experts [3]. While these techniques provide valuable localized measurements, they suffer from several inherent limitations. First, they are largely reactive, detecting instability only after predefined thresholds are exceeded. Second, threshold-based alarm systems are highly sensitive to noise, seasonal effects, and sensor drift, frequently leading to false alarms or missed early warning signals [4]. Third, most conventional systems operate on static thresholds and fail to capture the complex temporal evolution and cumulative stress mechanisms that govern slope degradation processes.

In response to these limitations, data-driven and machine learning-based methods have gained increasing attention in geotechnical hazard prediction. Supervised learning models such as linear regression, support vector machines, decision trees, and ensemble techniques have been applied to slope stability assessment using historical sensor data [5], [6]. Although these methods demonstrate improvements over rule-based approaches, they typically operate on static feature representations and lack the capability to model long-term temporal dependencies. Rockfall processes are inherently dynamic, influenced by gradual deformation, rainfall infiltration, pore pressure buildup, and micro-seismic activity evolving over time, making temporal modeling a critical requirement for accurate risk prediction [7].

Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have shown strong potential in modeling sequential data and capturing long-range temporal dependencies in various time-series forecasting tasks [8]. Recent studies have explored LSTM-based models for landslide and slope stability prediction, reporting improved predictive performance compared to traditional machine learning approaches [9], [10]. However, most existing works are limited by small datasets, site-specific assumptions, or lack integration with operational alerting and visualization frameworks. As a result, their practical deployment in real-world mining environments remains limited.

To address these gaps, this paper proposes an end-to-end AI-based rockfall prediction and alert system tailored for open-pit mining applications. A professionally engineered large-scale synthetic dataset is first developed to emulate realistic mine behavior across multiple zones, incorporating smooth risk transitions, zone-specific characteristics, and stochastic environmental influences. The dataset models key physical indicators including displacement, strain, pore pressure, vibration, rainfall, and temperature, enabling comprehensive representation of slope dynamics [11]. A multivariate time-series learning framework based on LSTM networks is then employed to predict a continuous risk index representing the likelihood of rockfall occurrence.

Beyond risk prediction, the proposed system introduces a robust risk scoring and alerting mechanism that combines rolling risk estimation, trend analysis, and baseline deviation to generate interpretable and actionable risk levels. Unlike conventional binary alarm systems, the proposed framework produces graded alerts (SAFE, WATCH, ALERT), reducing false positives while enabling proactive intervention [12]. Furthermore, the complete pipeline is deployed through an interactive Gradio-based dashboard, providing zone-wise visualization, real-time risk monitoring, and intuitive alert communication suitable for operational decision-making.

The main contributions of this work are summarized as follows:

- The design of a realistic, large-scale synthetic dataset that captures heterogeneous mine-zone behavior and mean-reverting temporal risk dynamics for rockfall modeling.
- The development of a temporal deep learning framework based on Long Short-Term Memory (LSTM) networks that outperforms classical machine learning baselines in continuous rockfall risk prediction.
- The integration of predictive modeling, trend-aware risk scoring, and real-time visualization into a unified, deployable decision-support system for open-pit mine safety.

Extensive experimental evaluation demonstrates the effectiveness, robustness, and practical relevance of the proposed approach, highlighting its potential as a scalable solution for enhancing safety in open-pit mining operations.

II. Literature Review

Rockfall prediction and slope stability analysis have long been central topics in geotechnical and mining engineering research. Early studies primarily relied on empirical observations, kinematic analysis, and physically based numerical models to evaluate slope failure mechanisms and hazard zones [1], [3]. While these approaches provide valuable insights into geological processes, they require extensive site-specific data and expert interpretation, making them unsuitable for continuous, real-time monitoring in large-scale open-pit mining environments.

With the widespread deployment of geotechnical sensors, threshold-based monitoring systems became a common practice for rockfall risk management. These systems trigger alarms when individual measurements such as displacement, pore pressure, or vibration exceed predefined limits [3], [4]. Although simple and computationally efficient, threshold-based methods suffer from significant drawbacks. They are highly sensitive to noise and environmental variability, lack adaptability to evolving site conditions, and fail to capture cumulative damage and delayed failure processes. Consequently, such systems often generate false alarms or miss early warning signs of instability.

To overcome the limitations of static thresholds, machine learning techniques have been increasingly applied to slope stability and landslide prediction. Classical supervised learning models, including linear regression, support vector machines, decision trees, and ensemble methods such as random forests, have been explored using historical geotechnical data [5], [6]. These methods demonstrate improved predictive performance compared to rule-based systems and are capable of modeling non-linear relationships among input variables. However, most classical machine learning approaches treat observations as independent samples and operate on snapshot features, ignoring the inherently temporal nature of slope degradation and rockfall precursors.

Recognizing the importance of temporal dependencies, recent studies have investigated time-series-based approaches for geohazard prediction. Long Short-Term Memory (LSTM) networks, originally introduced to address long-term dependency issues in sequential data [8], have been successfully applied in various time-series forecasting domains. Their ability to retain historical context makes them well-suited for modeling gradual deformation, pore pressure evolution, and rainfall-induced instability processes. Several works have reported improved performance of LSTM-based models for landslide and slope failure prediction compared to traditional machine learning techniques [9], [10]. Despite these advances, many existing studies are limited to small datasets, single-slope scenarios, or simplified experimental settings, reducing their applicability to complex, multi-zone mining operations.

Another critical challenge in this domain is the scarcity of labeled real-world rockfall datasets. Due to the rare and hazardous nature of rockfall events, comprehensive datasets are difficult to obtain, often restricted by safety, confidentiality, and cost considerations. To address this issue, some studies have employed synthetic or simulated data for model training and evaluation [11]. However, many synthetic datasets lack realistic temporal continuity or fail to represent smooth transitions between stable and critical states, which are essential for evaluating time-series prediction models and alerting mechanisms.

In addition to prediction accuracy, the practical deployment of rockfall monitoring systems requires reliable risk interpretation and alert generation. Existing research largely focuses on classification or regression performance, with limited attention given to transforming model outputs into actionable alerts suitable for operational decision-making [12]. The absence of trend-aware risk scoring, persistence-based alert validation, and intuitive visualization further limits the adoption of many proposed solutions in real mining environments.

In contrast to prior work, the present study adopts a holistic, system-oriented perspective. By combining a realistic zone-aware synthetic dataset, LSTM-based temporal modeling, professional risk scoring, and real-time visualization, the proposed framework addresses key gaps identified in existing literature. Unlike threshold-based or snapshot-driven approaches, the system explicitly models temporal evolution, zone heterogeneity, and alert reliability, positioning it as a practical decision-support tool for enhancing safety in open-pit mining operations.

III. Dataset Design and Synthetic Data Generation

Reliable rockfall prediction models require large-scale, high-quality time-series data capturing both geotechnical and environmental dynamics. However, real-world rockfall datasets are extremely scarce due to the infrequent and hazardous nature of failure events, site-specific confidentiality constraints, and the high cost of long-term monitoring campaigns [3], [11]. To address this limitation and enable systematic evaluation of temporal learning models, a realistic, professionally engineered synthetic dataset was designed in this study.

The dataset consists of 50,000 time-indexed samples representing multivariate sensor observations collected from an open-pit mine divided into five distinct zones. Each zone is designed to emulate a characteristic real-world behavior commonly observed in mining operations: (i) predominantly stable zones, (ii) rainfall-sensitive zones, (iii) vibration-sensitive zones, (iv) slow creep-dominated zones, and (v) mixed or highly variable zones. This zone-aware formulation enables the modeling of spatial heterogeneity, which is a critical yet often overlooked aspect of mine slope behavior.

Each data sample comprises six input features: surface displacement, internal strain, pore water pressure, micro-seismic vibration intensity, rainfall, and ambient temperature. These variables were selected based on their established relevance in slope stability analysis and rockfall hazard assessment [1], [3]. Rather than generating independent samples, the dataset follows a mean-reverting stochastic process, ensuring smooth temporal evolution of the underlying rockfall risk.

Figure 1 illustrates representative risk trajectories across the five mine zones, highlighting smooth transitions between normal, stressed, and critical states without abrupt jumps. This behavior closely mirrors real-world slope degradation processes such as gradual deformation, delayed rainfall response, and cumulative stress accumulation, which are essential characteristics for evaluating time-series prediction models.

The target variable is a continuous rockfall risk index bounded within the range [0,1], representing the relative likelihood of rockfall occurrence. Risk transitions are governed by probabilistic state dynamics corresponding to normal, stressed, and critical operating conditions, with smooth transitions preserved to maintain temporal continuity. The final dataset is evenly distributed across zones and time, enabling unbiased training and evaluation.

By explicitly modeling temporal continuity, zone-specific behavior, and realistic risk evolution, the proposed synthetic dataset provides a credible and reproducible testbed for developing intelligent rockfall prediction and alert systems, while remaining adaptable for future integration with real-world sensor data.

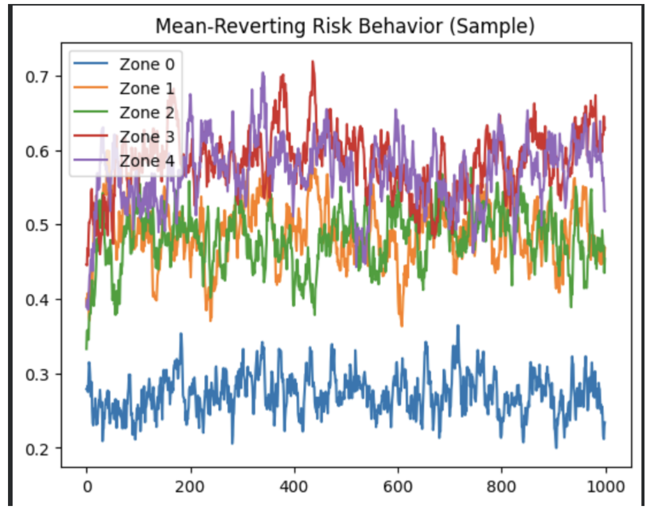

Fig. 1. Mean-reverting synthetic risk trajectories across five mine zones, demonstrating zone-specific behavior and smooth temporal transitions.

IV. Proposed Methodology

The proposed rockfall prediction framework is designed as an end-to-end, zone-aware system that converts multivariate geotechnical time-series data into interpretable risk assessments and operational alerts. The methodology consists of four sequential stages: (i) data preprocessing and time-series window construction, (ii) temporal risk prediction using a Long Short-Term Memory (LSTM) network, (iii) baseline machine-learning comparison, and (iv) integration with downstream risk scoring and alert generation. This structured pipeline ensures reproducibility, interpretability, and suitability for real-time deployment in open-pit mining environments.

Figure 2 presents the complete workflow of the proposed system, illustrating how raw zone-wise sensor data are transformed through preprocessing, temporal modeling, and risk interpretation into real-time visual alerts.

A. Data Preprocessing and Time-Series Windowing

All geotechnical and environmental input features—displacement, strain, pore pressure, vibration, rainfall, and temperature—are normalized using Min–Max scaling to ensure numerical stability during model training. Given the inherently sequential nature of slope degradation processes, a sliding window approach is adopted to construct time-series inputs. For each mine zone, overlapping windows of fixed length $T = 30$ time steps are generated, where each window captures recent sensor behavior leading up to a prediction instant.

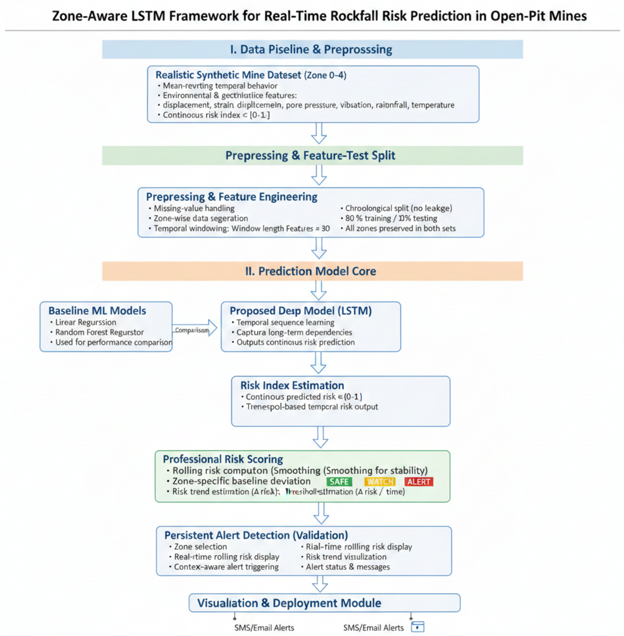

Fig. 2. End-to-end workflow of the proposed AI-based rockfall prediction and alert system, illustrating preprocessing, temporal modeling, risk scoring, and real-time visualization.

This windowing procedure transforms the original dataset into a three-dimensional tensor of shape (N, T, F), where N denotes the number of generated sequences, $T = 30$ represents the temporal window length, and $F = 6$ corresponds to the number of sensor features. The target output associated with each window is the continuous rockfall risk index at the final time step. To prevent spatial bias, the dataset is partitioned using a zone-stratified split, allocating 80% of the sequences for training and 20% for testing while preserving representation from all five mine zones.

B. LSTM-Based Temporal Risk Prediction

To model long-term temporal dependencies and gradual risk accumulation, a Long Short-Term Memory (LSTM) neural network is employed. LSTM architectures are particularly well-suited for time-series modeling due to their gated memory mechanism, which enables retention of historical context and mitigation of vanishing gradient issues [6], [7]. The proposed model consists of a single LSTM layer with 64 hidden units, followed by dropout regularization to reduce overfitting and a fully connected output layer with linear activation to predict the continuous rockfall risk index.

The model is trained using the Adam optimizer and Mean Absolute Error (MAE) loss, which provides robustness against occasional outliers while maintaining sensitivity to prediction accuracy. Early stopping based on validation loss is applied to ensure generalization. This configuration enables the model to learn smooth temporal patterns associated with progressive deformation, rainfall infiltration, and vibration-induced instability, rather than reacting to isolated sensor fluctuations.

C. Baseline Machine Learning Models

To evaluate the effectiveness of temporal modeling, two classical regression baselines are implemented for comparison: Linear Regression and Random Forest Regression. These models are trained on the same dataset after flattening each time-series window into a fixed-length feature vector. Linear Regression serves as a simple statistical baseline, while Random Forest captures non-linear feature interactions through ensemble learning [8], [9]. All models are trained and evaluated using identical data splits to ensure fair comparison.

D. Performance Evaluation

Model performance is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which quantify average prediction accuracy and sensitivity to larger errors, respectively. In addition to numerical metrics, qualitative analysis of predicted versus ground-truth risk trajectories is performed to assess temporal smoothness and trend fidelity, which are critical for reliable downstream risk scoring and alert generation.

V. Risk Scoring and Alert Generation

Accurate prediction of a continuous rockfall risk index alone is insufficient for operational decision-making in safety-critical mining environments. Raw model outputs must be transformed into interpretable and reliable alerts that balance early warning capability with false-alarm suppression. To address this requirement, a structured risk scoring and alert generation framework is developed on top of the LSTM-based predictions.

To reduce sensitivity to short-term noise, predicted risk values are first aggregated using a rolling temporal window, producing a smoothed rolling risk index. Since mine zones exhibit heterogeneous long-term behavior, a zone-specific baseline risk is computed using the median of historical rolling risk values, providing a robust reference for normal operating conditions. In addition to absolute risk magnitude, a risk trend metric is estimated to capture progressive risk escalation, which is a key precursor to slope instability.

Final risk levels are assigned by jointly considering rolling risk magnitude, deviation from the zone baseline, and trend direction. Based on these criteria, each time step is classified into one of three interpretable states: SAFE, WATCH, or ALERT. To further enhance reliability, ALERT conditions are required to persist across multiple consecutive windows before triggering an alarm. This trend-aware, persistence-based design reduces false positives and enables actionable early warning, aligning with best practices in geotechnical risk monitoring systems [3], [12].

VI. Experimental Results and Discussion

This section presents a comprehensive evaluation of the proposed zone-aware rockfall prediction and alert system, focusing on prediction accuracy, comparative performance against baseline models, and validation of the risk scoring and alert generation framework. All experiments are conducted on the professionally designed synthetic dataset described in Section III, using a zone-stratified train–test split to ensure balanced representation across all mine zones.

A. Prediction Performance Evaluation

The predictive performance of the proposed LSTM-based model is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are standard metrics for continuous risk prediction tasks. These metrics capture both average prediction accuracy and sensitivity to larger errors. The proposed approach is compared against two classical regression baselines: Linear Regression and Random Forest Regression. For fair comparison, baseline models are trained on flattened time-series windows derived from the same dataset.

Table I summarizes the quantitative performance of all evaluated models. The LSTM-based model achieves the lowest error values, with a test MAE of **0.019** and RMSE of **0.024**, outperforming Linear Regression (MAE 0.0221, RMSE 0.0278) and Random Forest Regression (MAE 0.0310, RMSE 0.0389). These results highlight the importance of explicit temporal modeling for capturing gradual risk accumulation and delayed effects inherent in geotechnical processes.

B. Quantitative Performance

TABLE I
MODEL PERFORMANCE COMPARISON

Model	MAE	RMSE
Linear Regression	0.0221	0.0278
Random Forest	0.0310	0.0389
LSTM (Proposed)	**0.0190**	**0.0240**

C. Qualitative Analysis of Temporal Predictions

Beyond numerical accuracy, the temporal behavior of model predictions is critical for safety-critical applications. Figure 3 illustrates representative predicted and ground-truth risk trajectories for a selected mine zone. The proposed LSTM model closely follows the underlying risk evolution, accurately capturing smooth transitions between normal, stressed, and elevated risk states without exhibiting abrupt oscillations or prediction lag.

This smooth tracking behavior is particularly important for downstream alert generation, as it reduces sensitivity to transient noise while preserving meaningful upward trends associated with progressive slope instability. In contrast, baseline models exhibit limited ability to capture temporal continuity due to their reliance on static feature representations.

D. Zone-Wise Risk Behavior

The zone-aware formulation enables differentiated risk behavior across the mining site. Experimental results confirm that different zones exhibit distinct baseline risk levels and variability consistent with their designed characteristics, such as rainfall sensitivity, vibration sensitivity, or creep-dominated behavior. This demonstrates that the model does not enforce a uniform response across all zones but instead learns localized temporal patterns, which is essential for large-scale open-pit mining environments.

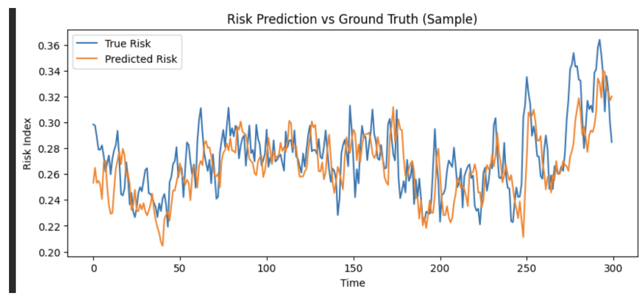

Fig. 3. Predicted and ground-truth rockfall risk index for a representative mine zone.

E. Validation of Risk Scoring and Alert Framework

To assess the practical reliability of the alerting mechanism, the distribution of assigned risk levels (SAFE, WATCH, ALERT) is analyzed across zones and time. The majority of observations are classified as SAFE, with WATCH states appearing during moderate deviation from baseline conditions. ALERT states are comparatively rare and occur primarily during periods of sustained risk escalation combined with a positive risk trend.

This distribution validates the effectiveness of the rolling aggregation, zone-specific baseline normalization, and persistence-based alert logic in suppressing false alarms while maintaining sensitivity to genuine risk escalation. The framework successfully transforms continuous model predictions into interpretable and actionable alerts suitable for operational decision-making.

F. Discussion

Overall, the experimental results demonstrate that the proposed framework achieves superior predictive accuracy while delivering stable, interpretable, and operationally meaningful risk assessments. By integrating temporal deep learning with zone-aware risk interpretation and alert validation, the system addresses key limitations of threshold-based and snapshot-driven approaches, reinforcing its suitability for deployment in real-world open-pit mining environments.

VII. SYSTEM ARCHITECTURE AND DEPLOYMENT

The proposed rockfall prediction framework is implemented as an end-to-end decision-support system integrating temporal risk prediction, risk scoring, and real-time visualization. The system architecture follows a modular design comprising three main components: the trained LSTM-based inference model, the risk scoring and alert generation module, and an interactive monitoring dashboard.

During operation, incoming zone-wise sensor data are processed in fixed-length temporal windows and normalized using the same preprocessing pipeline applied during training. Each window is passed through the trained LSTM model to generate a continuous rockfall risk prediction. The predicted risk values are then forwarded to the risk scoring module, where rolling aggregation, zone-specific baseline deviation, and trend analysis are applied to determine the current risk state.

To enable practical usage and demonstration, the complete pipeline is deployed using a Gradio-based interactive dashboard. The dashboard allows users to select individual mine zones and view the corresponding rolling risk values, assigned risk levels (SAFE, WATCH, ALERT), and recent risk trends. This interface provides intuitive visualization and facilitates rapid situational awareness for mine operators.

Figure 4 shows a screenshot of the deployed dashboard interface. The lightweight and modular design of the system enables easy integration with live sensor streams, cloud-based analytics platforms, or edge deployment environments in future implementations.

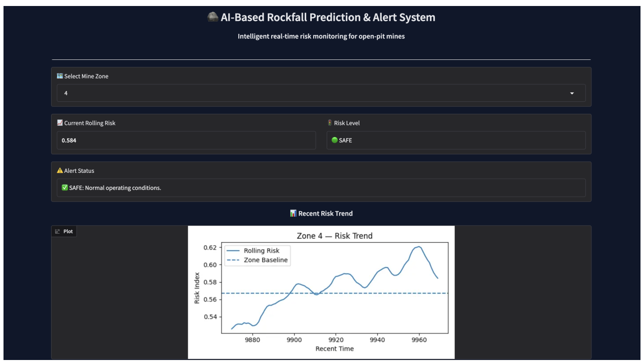

Fig. 4. Gradio-based dashboard for real-time zone-wise rockfall risk monitoring.

VIII. Conclusion and Future Work

This paper presented a zone-aware AI-based framework for rockfall risk prediction and alert generation in open-pit mining environments. By combining a professionally designed mean-reverting synthetic dataset with LSTM-based temporal modeling, the proposed system effectively captures gradual risk evolution and zone-specific behavior that are often missed by conventional threshold-based approaches. Experimental results demonstrate that the proposed model outperforms classical machine learning baselines in continuous risk prediction, while producing stable and interpretable outputs suitable for downstream alerting.

Beyond prediction accuracy, the integration of rolling risk aggregation, trend analysis, and persistence-based alert logic enables reliable transformation of model outputs into actionable risk states. The deployment of the framework through an interactive dashboard further demonstrates its practical applicability for real-time monitoring and decision support in mining operations.

Future work will focus on validating the proposed approach using real-world sensor data, extending the framework to incorporate additional geotechnical parameters, and exploring advanced temporal architectures such as attention-based models. Integration with live sensor streams and edge computing platforms will also be investigated to support large-scale, real-time deployment.

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