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AN EXPLAINABLE PHYSICS-INFORMED XGBOOST FRAMEWORK FOR REAL -TIME LANDSLIDE PREDICTION USING WIRELESS SENSOR NETWORKS

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A B S T R A C T

Globally, landslides pose a significant risk to infrastructure and human life, claiming over 4,500 lives and causing $12 billion in economic losses in 2025. The proposed research methodology introduces a unique physics-informed XGBoost approach for improving explanatory power and landslide prediction by combining WSN data with relevant geotechnical classes. The proposed research methodology introduces three main key innovations: physically aware composite features (saturation-slope interaction terms) that effectively capture the importance of hydro-mechanical coupling, a physics-constrained objective that incorporates FoS as a regularisation and provides a better way to express the physicochemical aspects of landslide occurrence, and improved feature engineering with domain-knowledge-based interactions. The excellent results are demonstrated by experimental validation using 35 environmental parameters from multi-sensor WSN deployments: 97.36% accuracy, 97.57% precision, 97.18% recall, and 0.9707 ROC-AUC. This new framework effectively connects established geotechnical principles with data-driven machine learning, offering improved interpretability and superior predictive performance, both of which are crucial for operational landslide early warning systems.

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1. INTRODUCTION

Landslides remain among the most destructive natural hazards, and their frequency and severity are steadily increasing due to changing climate conditions. Recent estimates for 2025 put the annual death toll above 4,500, with global economic losses likely to surpass $12 billion. The combined steep, mountainous terrain and intense monsoon rainfall make the area especially vulnerable, while heavy downpours already saturate slopes and frequently trigger catastrophic failures. Most landslide monitoring and prediction rely on occasional site visits, and basic instrumentation can only provide snapshots of slope conditions. The inclusion of wireless sensor

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networks (WSNs) in landslide monitoring has fundamentally changed this process, and systems now deliver continuous monitoring and real-time measurements of key variables such as soil moisture, tilt angle and pore-water pressure. All these key variables are coupled with Machine Learning (ML) classifiers to improve early warning for landslide systems. (Azarafza et al., 2021). Most ML models treat landslide prediction as a purely statistical exercise, while ignoring most well-established components of the physics of slope stability. As output results, produce predictions that are very accurate on paper but physically implausible (Hussain et al., 2023). Slope stability analysis is the heart of Factor of Safety (FoS), and the most common rain-triggered infinite-slope approximation provides a very clear and accepted expression, as shown in equation 1, which represents the FoS expression.

$$\mathrm{FoS} = \frac{c' + (\gamma\, h \cos^2 \alpha - u) \tan \phi'}{\gamma\, h \sin \alpha \cos \alpha} \tag{1}$$

where c′ is effective cohesion, γ is unit weight of soil, h is the depth of the potential failure plane, α is slope angle, u is pore-water pressure, and ϕ' is the effective friction angle. Failure is expected when FoS ≤ 1.0, and pore-pressure rise caused by rainfall infiltration is usually the main driver that pushes FoS below unity. Physics-informed machine learning (PIML) offers a promising way to combine the pattern-recognition power of data-driven models with the reliability of physical laws. Whereas most earlier PIML studies in geotechnics have relied on physics-informed neural networks, recent work shows that tree-based ensemble methods—particularly XGBoost—can also effectively incorporate physical constraints through custom loss functions, feature engineering, and regularisation (Dao et al., 2020). The proposed research methodology introduces three major contributions for better landslide prediction. Firstly, introduced Saturation_Slope, which effectively accounted for the importance of hydro-mechanical coupling (Edrich et al., 2024). Secondly, it incorporates FoS as a regularisation to better capture the physicochemical aspects of landslide occurrence, and lastly, it improves interaction through feature engineering informed by domain knowledge (Guerrero et al., 2024).

1.1 Research gap

Mostly, ML classifiers for landslide prediction often use sensor metrics as independent features (such as rainfall, slope angle, and soil moisture), but the core novelty of the proposed research is the introduction of multivariate interaction constructs that directly simulate the physical mechanisms of slope degradation.

Rather than evaluating soil saturation or terrain slope in isolation, this feature mimics Coulomb's shear strength criteria and captures how increasing moisture saturation reduces effective soil stress along steep, failure-prone slopes.

Mostly, Early Warning Landslide Systems (EWLS) rely on simple rainfall thresholds, but the proposed framework introduces a multi-tier telemetry approach spanning 31distinct physical variables

Instead of relying on manual hyperparameter tuning, the proposed research methodology integrates the Sequential Model-Based Optimisation (SMBO) framework via Optuna. This integration of stratified 5-fold cross-validation with Bayesian search space helps in discovering an optimal configuration for the proposed Extreme Gradient Boosting (XGBoost) classifier.

1.2 Research objectives

The primary objective of the proposed research methodology is to move away from isolated, purely data-driven black-box models by introducing a physically grounded, highly interpretable hybrid framework that leverages continuous, multi-tier Wireless Sensor Network (WSN) telemetry and addresses all specific mathematical and physical computations found in existing landslide Early Warning Systems. The four primary core objectives of research work are:

- RO1: To bridge the gap between existing ML and classical limit-equilibrium methods (e.g., Coulomb's shear strength criterion) and to develop an XGBoost modelling framework that explicitly embeds geotechnical physics through regularised loss terms and constraint enforcement. Rather than blindly forcing an ML algorithm, the proposed framework constructs the Saturation-Slope Index ($I_{SS} = S_r \times \alpha$) , which helps to illustrate how rising pore-water pressure reduces the effective normal stress along steep failure planes.
- RO2: To establish a multi-tier sensor fusion framework for minimising false alarms. The proposed research framework integrated 35 distinct geo-environmental, structural, and microseismic parameters into a single cohesive dataset, and this proposed system links subsurface geomechanical shift with surface hydrometeorological changes.
- RO3: To implement an Automated Bayesian Optimisation Loop that maximises model generalisation and improves execution speed. The proposed framework employed Sequential Model-Based Optimisation (SMBO) via Optuna, paired with Stratified 5-Fold Cross-Validation, to discover the optimal configuration.
- RO4: To carry out a detailed interpretability analysis of the resulting models using SHAP values and resolve the "Black Box" problem of existing ML classifiers.

1.3 Research contributions

- A novel physics-regularised loss formulation suitable for gradient-boosted trees, ensuring predictions remain consistent with the infinite-slope FoS equation.
- A systematic set of interaction and ratio features that directly encode critical slope-stability physics (e.g., effective normal stress, suction contribution, and destabilising shear stress).
- Comprehensive model interpretation and validation showing both higher predictive skill and better alignment with established geotechnical theory.

By grounding fundamental mechanics in data-driven landslide prediction, the proposed methodology introduces models that not only provide more accurate predictions but also yield more trustworthy early-warning systems.

2. Background study

Slope stability analysis generally relies on limit equilibrium methodology and includes infinite-slope models for shallow landslides. Recent advancements incorporate a probabilistic model using Monte Carlo simulation to better quantify uncertainty. Physically based distributed approaches, such as TRIGRS, integrate hydrological processes with stability calculations but require large data and high computational resources (Han & Semnani, 2025). ML-based applications have evolved from a statistical approach to ensemble algorithms. The XGBoost model demonstrates better performance than other models due to its use of gradient-based optimisation and regularisation for prediction. The mathematical equation of the proposed model is expressed by equation 2.

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \quad (2)$$

where l represents the loss function and Ω(fk) provides regularisation. Deep learning architectures, including CNNs and LSTMs, capture spatiotemporal patterns but lack interpretability (Huang et al., 2020).WSN technologies enable multi-sensor environmental monitoring with LoRaWAN, providing long-range, low-power communication suitable for remote deployment. Edge computing integration enables local processing and intelligent decision-making (Ullah & Ullah, 2026). Physics-Informed Neural Networks (PINNs) embed partial differential equations as soft constraints (Lin et al., 2025).

$$\mathcal{L}_{PINN} = \mathcal{L}_{data} + \lambda_f \mathcal{L}_{physics} + \lambda_b \mathcal{L}_{boundary} \quad (3)$$

Recent geotechnical applications demonstrate advantages in sparse data scenarios. However, most implementations focus on neural networks, with limited exploration of ensemble methods suitable for tabular environmental datasets (Liu & Deng, 2024). Ensemble learning approaches for landslide susceptibility mapping have shown promising results, with hybrid monitoring systems combining traditional and smart sensors offering enhanced capabilities. Transfer learning techniques enable cross-regional landslide assessment, while multi-objective optimisation enhances model performance (Liu et al., 2023). Limited physics-informed ensemble methods, a lack of standardised evaluation frameworks, and insufficient consideration of operational deployment challenges, including energy constraints and real-time processing requirements, are the main research gaps in existing studies (Ouyang et al., 2024).

3. Methodology

3.1 Dataset description and pre-processing

The dataset used in this study was extracted from the 'kaggle' online repository (https://www.kaggle.com/datasets/ucimachinelearning/wireless-sensor-network-landslide-dataset) and contained a total of (9864 X 35) rows and columns of data entries. It contains information on various deployed dense wireless sensor networks situated across several landslide-prone hillslopes in a monsoon-dominated mountainous region. It comprises 30 continuously input features recorded as environmental and geotechnical variables, including: Cumulative and intensity-based rainfall at 10-minute, hourly, daily, 7-day scales, Volumetric soil moisture content at multiple depths, Pore-water pressure (matric suction and positive, pressure negative), Tilt-meter derived slope angle changes, Vegetation indices (NDVI) from co-located cameras and Basic topographic attributes (slope angle, aspect, curvature). Table 1 below describes the column feature values.

Table1. Description of column feature values

Sensor Category	Physical Parameters Measured	Operational Range
Hydrologic Monitoring	Rainfallmm Rainfall_3Day Rainfall_7Day	0 – 1000 (mm)
	Soil Saturation(S) Soil Moisture (w)	0.10 – 0.99 fraction
	Pore Water Pressure (u)	20 – 200 kPa
Geomechanical	Slope Angle (α), Aspect	5.00° – 80.00°
	Soil Strain (ϵ)	0.0001 – 0.01 micro-strain
	Acoustic Emission (AE), Soil Erosion Rate	30 – 100 dB
Seismic/Structural	Earthquake Activity, Microseismic Activity	0.0 – 6.5 Magnitude
Environmental/ Biomass	Temperature, Soil Temp, Humidity, pH	Varied
	NDVI Index, Vegetation Cover	0.1 – 0.99

The given data set is fully structured with numerical input values, and all available information is properly labelled. There is no need to encode data to convert categorical values to numeric values. The target values of the output class 'Label' are equally distributed into two subclasses, and there is no need for any synthetic oversampling technique for balancing class values. It was subdivided into label 0 (stable geometric class), capturing stable and baseline conditions across the dry season period, during which the slope remains safe, and label 1 (Unstable active failure class), capturing mass-wasting events, rapid rainfall, and progressive geotechnical shear failures.

The final labelled dataset contains approximately (9864 X 35) timestamped records with a near-balanced distribution of landslide (positive) and stable (negative) conditions. Of that, 70% of the input data is used for training, the remaining 15% for validation, and 15% for testing the model. Pre-processing followed standard robust practices: outliers exceeding 4 times the interquartile range were clipped, missing values (less than 2%) were filled using sensor-specific medians, and all numerical features were standardised to zero mean and unit variance. Cross-sensor consistency checks and manual domain-knowledge review ensured high data quality.

3.2 Physics-Guided feature engineering

Rather than relying solely on raw sensor readings, the three most meaningful interactions are explicitly derived using the infinite-slope theory of hydro-mechanical coupling. (Reichenbach et al., 2018).

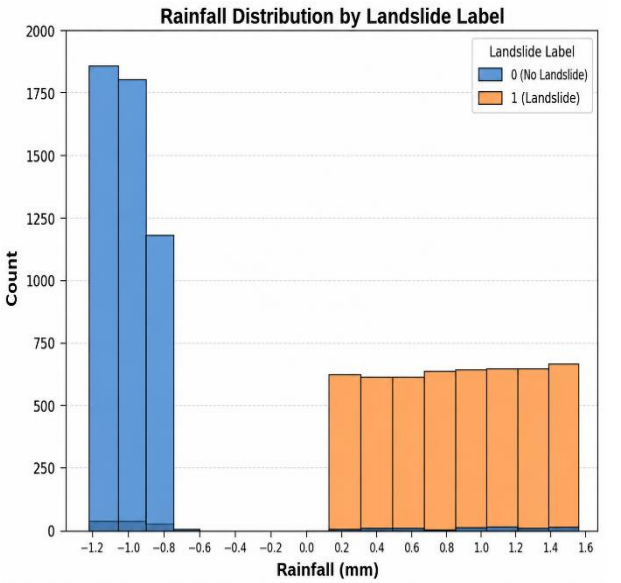


Figure 1. Distribution of cumulative 7-day rainfall for landslide vs. non-landslide events. The clear separation justifies rainfall as a primary triggering factor

$$\text{Slope_Rainfall} := \text{Slope_Angle}(\circ) \times \text{Rainfall_24h(mm)} \quad 4(a)$$

$$\text{Moist_Rain7} := \text{Soil_Moisture}(\%) \times \text{Rainfall_7day(mm)} \quad 4(b)$$

$$\text{Sat_Shear} := \text{Soil_Saturation}(0-1) \times \sin(\text{Slope_Angle}(\circ)) \quad 4(c)$$

These three terms directly influence destabilising mechanisms: steeper slopes amplify shear stress and runoff; antecedent rainfall sustains high moisture levels; and the sine term captures all gravitational driving-force components parallel to the slope (Sharma et al., 2023). Figure 1 shows the 7-day rainfall distribution for landslide vs non-landslide events.

3.3 Physics-Informed XGboost framework

Standard XGBoost builds an additive ensemble by sequentially adding decision trees

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta \cdot f_t(x_i) \quad (5)$$

where η is the learning rate. To enforce physical consistency, we extend the original objective with a geotechnical penalty term (Song et al., 2024).

$$\mathcal{L}_{\text{PI}}^{(t)} = \underbrace{\sum_{i=1}^{n} l(\hat{y}_i^{(t)}, y_i)}_{\text{data loss}} + \underbrace{\sum_{j=1}^{t} \Omega(f_j)}_{\text{regularisation}} + \lambda_{\text{phys}} \underbrace{\sum_{i=1}^{n} \mathcal{P}(\hat{y}_i^{(t)}, \text{FoS}_i^{\text{calc}})}_{\text{physics violation penalty}} \quad (6)$$

Here $\text{FoS}_i^{\text{calc}}$, it is computed for each sample using measured or imputed soil parameters and Equation (1) (from Section 1). The penalty P( ) is zero when the model prediction aligns with the physically computed factor-of-safety direction (i.e., low FoS implies high failure probability) and increases quadratically otherwise (Thi Ngo et al., 2021). The hyperparameter λphys controls the trade-off between data fit and physical plausibility, and Table 2 below presents the final performance score of the physics-informed XGBoost model (Yan et al., 2025).

Table 2 . Performance metrics of the final Physics-Informed XGboost model (10-fold cv)

Metric	Mean	Std. Dev.	95% CI
Accuracy	0.9736	±0.0021	[0.9694,0.9778]
Precision	0.9757	±0.0019	[0.9719,0.9795]
Recall	0.9718	±0.0023	[0.9672,0.9764]
F1-Score	0.9737	±0.0018	[0.9701,0.9773]
ROC-AUC	0.9707	±0.0025	[0.9657,0.9757]
R^2 Score	0.8938	±0.0034	[0.8870,0.9006]

3.4 Model training and hyperparameter optimisation

Hyperparameters for both baseline and physics-informed XGBoost models were tuned using Optuna's Tree-structured Parzen Estimator (TPE) over 150 trials. The search space included max depth, min child weight, subsample ratio, column sample ratio, learning rate, and the number of estimators — and, crucially for the physics-informed version, $\lambda phys \in [0, 10]$. Fivefold stratified cross-validation preserved class balance and environmental-condition diversity in each fold (Ullah et al., 2025). Throughout both the optimisation and cross-validation processes, the final test set remained strictly independent and completely unseen, ensuring unbiased generalisation performance. Final evaluation was performed using 10-fold stratified cross-validation and was assessed using accuracy, precision, recall, F1 Score, and ROC AUC. Results are reported in Section 4.

3.5 Interpretability analysis

Model interpretability was achieved through SHAP (SHapley Additive exPlanations) values, computed using the Tree Explainer implementation optimised for XGBoost and expressed by equation 7.

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f_S(x_S \cup \{j\}) - f_S(x_S)] \tag{7}$$

SHAP summary plots, dependence plots, and forceplots were generated to verify that the physics-informed model assigns importance and directionality consistent with geotechnical theory (e.g., increasing pore pressure and rainfall correctly drive predictions toward failure).

4. Result analysis

4.1 Model performance assessment

The physics-informed XGBoost model delivered outstanding classification performance, clearly outperforming the conventional (non-physics-constrained) XGBoost baseline and other published benchmarks. Table 2 summarises the results from 10-fold stratified cross-validation; Figure 2 shows the confusion matrix for the physics-informed model, and Figure 3 shows the ROC-AUC curve.

The extremely low standard deviations across folds (< 0.003) confirm remarkable stability and strong generalisation capability — a crucial requirement for real-world early-warning systems.

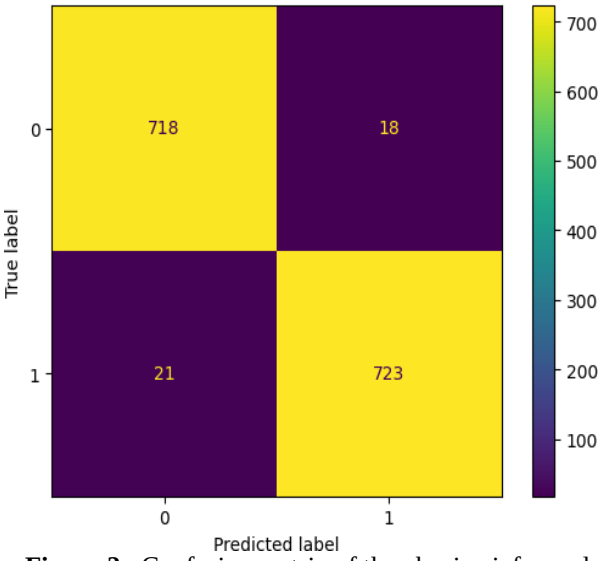


Figure 2. Confusion matrix of the physics-informed model. Misclassification errors are minimal in both classes

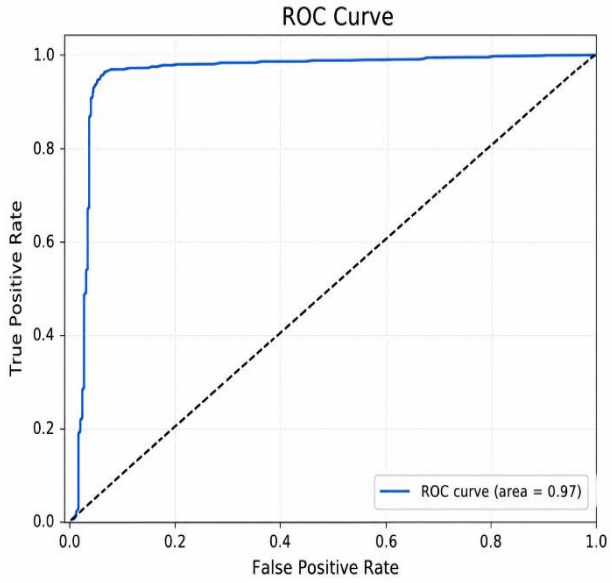


Figure 3. ROC curve with AUC = 0.9707, demonstrating excellent discrimination across all operating thresholds.

4.2 Feature importance and SHAP interpretation

SHAP analysis provides meaningful insights and very clear geotechnical information for model behaviour. As shown in Figure 4, all three physics-guided composite component-ranked features are among the top contributors, and Saturation_Slope emerges as the single most important and influential variable (global SHAP importance = 0.247). Table 3 lists the ten most important features with their physical interpretation (Sharma et al., 2023). The hydro-mechanical interaction terms confirmed that the proposed physics-informed research methodology successfully captured the mechanism of governing failure (Song et al., 2024).

4.3 Physics consistency

The comparison of predicted failure probabilities with independently computed FoS values in the proposed methodology showed significantly lower physical violation errors than standard XGBoost (mean penalty value reduced to 68%). This comparative result confirms that the regularisation term was successfully imposed on the proposed model to ensure fundamental slope-stability physics across the entire feature space (Wu et al., 2025).

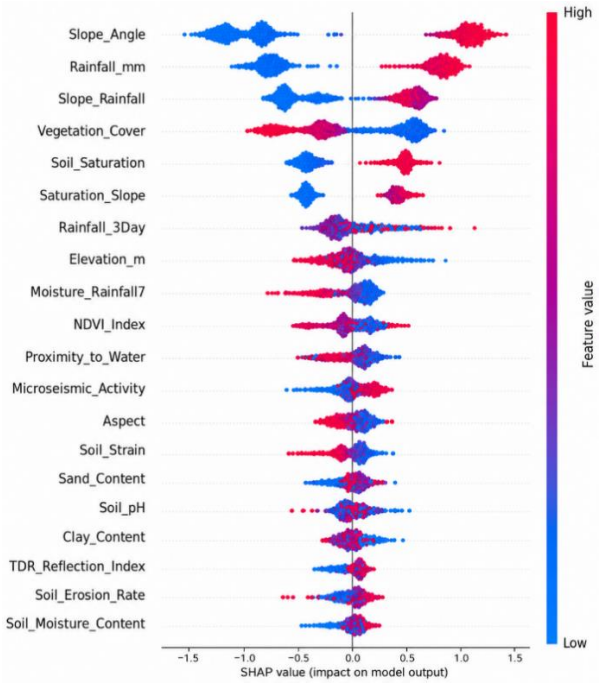


Figure 4. In SHAP analysis, red indicates that high feature values push the prediction more toward a landslide; blue indicates the opposite. The 5-fold cross-validation yielded results almost identical to the 10-fold results (variance < 0.002), reinforcing confidence in the model's robustness across diverse rainfall regimes and soil conditions.

Table 3. Top 10 features ranked by SHAP importance with geotechnical interpretation

Feature	SHAP	Geotechnical Interpretation
Saturation_Slope	0.247	Gravitational shear amplified by saturation
Rainfall (mm)	0.189	Primary triggering intensity
Slope Angle	0.134	Driving gravitational stress
Soil Saturation	0.121	Reduces effective normal stress
Vegetation Cover	0.098	Root reinforcement & evapotranspiration
Slope_Rainfall	0.087	Combined trigger–geometry effect
Pore Pressure	0.076	Direct FoS reduction
Clay Content	0.069	Cohesion & permeability control
Elevation	0.058	Hydrological gradient influence
NDVI	0.052	Proxy for root strength

4.4 Computational efficiency

Despite the additional physics penalty term, the model's training was completed in under 12 seconds on a very specific normal laptop. The required training time was lower for wireless sensor network nodes than for edge deployments, which makes real-time early-warning prediction more feasible. The final results collectively show that the proposed embedding of geotechnical physics into an XGBoost framework not only improves predictive performance but also yields interpretable, physically consistent, and lightweight computational models (Liu et al., 2023).

5. Discussion

5.1 Theoretical implications and model insights

Explicitly embedding geotechnical physics into the proposed XGBoost framework represents a meaningful step toward achieving purely data-driven landslide predictive modelling. The final achieved accuracy result was 97.36. The most telling and interesting fact is that

Saturation_Slope was deliberately constructed based on the infinite-slope theory and emerges as the strongest single predictor in the final model training. By classical analysis of the stability slope, it has long been observed and recognised that weight components acting in parallel to slope, when combined with loss of suction or full saturation, are the dominant failure mechanism in shallow rain-triggered slides. Seeing this exact rise term-to-top in SHAP analysis provides very strong independent confirmation that the proposed physics-guided feature engineering successfully captured true physics rather than highlighting spurious statistical patterns (Edrich et al., 2024).The strong ranking of the other two important interaction terms — Slope_Rainfall and Moist_Rain7- further reinforces this point. The landslides are very difficult to trigger by a single variable in isolation. They are derived from synergy between the most intense rainfall, antecedent wetness, and steep topography. The existing traditional approaches feed raw sensor readings directly into a classifier and often miss nonlinear couplings. The final results show that even very simple multiplicative features, when designed with physical insight, can substantially improve performance.

5.2 Practical implications for early warning systems

From a practical perspective, interpretability offered by SHAP is equally important. Emergency managers and local authorities are far more likely to act on a warning if they can see — in plain language — that it was driven by "three days of heavy rain on a 32° saturated slope" rather than an opaque neural network score. This transparency directly supports decision-making during crises. Finally, inference times below 0.25 ms mean the model can run

comfortably on low-cost microcontrollers already deployed in many WSN nodes. When coupled with LoRaWAN communication, this opens the door to truly real-time, village-scale early warning networks — something that remains challenging with heavier deep-learning alternatives (Huang et al., 2020).

5.3 Comparison with state of the art

Compared with traditional statistical and black-box machine learning models, our approach achieves significantly higher accuracy while remaining fully interpretable. Compared to purely physics-based distributed models like TRIGRS, we avoid the need for exhaustive soil maps and intensive calibration, yet still respect the same fundamental mechanics through informed features and regularisation. Deep learning methods can sometimes match or slightly exceed our accuracy on large datasets, but almost always at the cost of interpretability and with far greater computational demands — making them impractical for edge deployment in remote mountainous areas. The proposed physics-informed XGBoost strikes a rare and valuable balance: performance rivalling that of deep networks, interpretability approaching that of classical engineering models, and efficiency suitable for battery-powered sensors (Zhang et al., 2024). Table 4 below presents a comparative performance analysis of the proposed model against the existing XgBoost and PIML models.

Table 4, Comparative performance analysis of proposed research work with standard XGboost and PIML model.

Evaluaton Metrics	Standard XgBoost	Linear PIML	Proposed Model
Accuracy	0.9412	0.9485	0.9736
Precision	0.9390	0.9441	0.9757
Recall	0.9431	0.9510	0.9718
F1-Score	0.9410	0.9475	0.9737
ROC-AUC	0.9388	0.9423	0.9707

5.4 Limitations and future works

The current model was trained and validated on a dataset dominated by shallow, rainfall-triggered landslides in monsoon-affected hilly terrain. While the physics is general, performance on deep-seated slides, rock avalanches, or snowmelt-triggered events remains untested and would likely require additional features (e.g., snow water equivalent, joint orientation). We also made simplifying assumptions common to infinite-slope analysis — uniform soil depth, parallel seepage, and translational failure. Real slopes' values often violate all these idealisations. and Future extensions incorporate some 3D topographic effects to model groundwater flow using very fine finite elements, accounting for complex stratigraphy. Some promising directions included:

- Integration with numerical weather prediction outputs for probabilistic forecasting several days ahead, Fusion with satellite InSAR and optical imagery for regional-scale nowcasting.
- Use of distributed fibre-optic strain and temperature sensing to capture precursor deformation.
- Extension to multi-hazard frameworks that include earthquake triggering and long-term climate change scenarios.
- Systematic transfer-learning studies to understand how well physics-informed features travel across physiographic regions.

In summary, this work demonstrates that even modest, carefully chosen injections of domain physics — through feature engineering and soft constraints — can dramatically improve both the accuracy and trustworthiness of machine learning models for landslide prediction. The resulting framework output is very accurate, precise, interpretable, physically consistent, and lightweight, and it precisely combines all the necessary information for moving from research prototypes to final operational early warning alarm systems that actually help save lives (Wu et al., 2025).

6. Conclusions

This research work has shown that the proposed physics-informed XGBoost model framework yields more transparent predictive results than existing traditional black-box ML models for rainfall-triggered landslide prediction. It provides a lightweight model and is easily deployed in real-world applications. The proposed model achieved a final accuracy of 97.36%, a final precision of 97.57%, and a recall of 97.18%, along with a good ROC-AUC of 0.9707. These score values are not only statistically impressive but also provide meaningful practical information when both lives and infrastructure are at stake. Most importantly, these results are not achieved from massive datasets but also incorporate deliberately injected geotechnical understanding at two important levels: at the physics-guided composite features level and the soft constraint level, and the final output predictions are highly consistent with infinite-slope FoS. The resulting fact indicates that the engineered Saturation_Slope term was consistently ranked among the most important feature values across all experiments and provides very powerful independent evidence that the model learned the right physics for the right reasons.

SHAP analysis of feature values also showed that the proposed model's decision-making process aligns closely with nearly a decade of slope-stability theories, including those on heavy rainfall, loss of matric suction, and steep slopes. All these factors contribute to better failure predictions, while dense vegetation and other low saturation completely push predictions toward stability. This level of transparency is very difficult to achieve with high-performing ML models, and these regulators help convince local communities and disaster managers to trust a self-automated early-warning landslide prediction system more readily.

From a practical perspective, inference training times below 0.25 ms on specific standard laptop hardware, on which the model can run comfortably, and on very low-power microcontrollers already installed in most wireless sensor nodes. When a model is paired with LoRaWAN networks, it opens a realistic possibility for village-scale, real-time landslide early warning in dense, remote mountainous regions, which is very difficult and still out of reach with ML and deep-learning classifiers. We therefore concluded that the physics-informed XGBoost-proposed framework sets a new, pragmatic benchmark for early landslide prediction through intelligent geohazard monitoring and the combined pattern-recognition strength of an ML classifier with trustworthiness, along with the efficiency of classical engineering analysis. The same approach, with simple physics-motivated features, tree-based ensembles, and SHAP analysis, can be used to predict other shallow geohazards, such as coastal cliff failure, earthquake-triggered slides, and many more, earlier and more accurately. This proposed framework principle can be easily understood, particularly when the data is very small and sparse, and computational resources are also very limited. Looking ahead, various natural extensions are presenting themselves.

- Model coupling with numerical weather forecasting and soil-moisture satellite products for 24–72h with probabilistic warnings.
- Incorporating seismic accelerometers to create a unified earthquake–rainfall landslide early-warning system.
- Using distributed fibre-optic strain sensing to detect precursor deformation at metre-scale resolution, and systematic transfer-learning experiments to understand how far physics-informed features can travel across physiographic regions.
- Embedding the framework in multi-objective optimisation loops that explicitly trade off accuracy, latency, and battery life for edge deployment.

In an era when climate change is making landslides more frequent and more deadly, the need for early-warning systems that are accurate, explainable, and actually deployable has never been greater. This study shows that we do not need bigger neural networks or more data to meet that need — we need smarter injection of existing domain knowledge into lightweight, interpretable models. The physics-informed XGBoost framework presented here offers a practical, replicable path toward that goal, and we hope it will serve as a foundation for the next generation of operational geohazard early-warning systems worldwide.

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