Machine Learning-Based Landslide Risk Prediction in Tirana, Albania

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Landslides represent a significant natural threat to human life and infrastructure in mountainous regions worldwide, particularly in areas experiencing rapid urbanization and environmental pressures. This article presents a data-driven approach to landslide susceptibility prediction in the Tirana region of Albania using machine learning. Historical landslide occurrence data (252 landslide events) and non-landslide control points (300 locations) were compiled for Tirana region, with geospatial predictor features including topographic, geological, seismic, and hydrological factors. Three machine learning models, Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) were developed and evaluated. XGBoost achieved the highest prediction accuracy (94.2%), meanwhile RF (94.1%) and SVM (91.3%) on the test set. It also attained excellent precision (92.5%) and recall (96.1%), corresponding to an F1-score of 0.94 and area under ROC curve (AUC) of 0.99. The results demonstrate that machine learning can effectively identify landslide-prone areas in the Tirana region, which is notable as this represents the first such predictive model for landslide risk in Albania. The model outcomes can support local authorities in early warning, spatial planning, and risk mitigation.

Keywords—landslide prediction, Tirana, Albania, machine learning, XGBoost, Random Forest, Support Vector Machine

I. Introduction

Landslides pose a major threat to infrastructure and human life in regions with mountains and high rainfall [1]. Factors contributing to increased landslide occurrence include climate change, extreme rainfall, population distribution, and human activities such as construction and mining [2] [3]. Albania faces particularly acute landslide risks due to its complex geological structure, mountainous terrain, and increasing environmental pressures [4]. Traditional methods for risk assessment, such as expert systems and geotechnical models, are resource-intensive and limited by human subjectivity. With the advent of artificial intelligence (AI), machine learning (ML) and deep learning (DL) methods have become prominent in landslide detection, offering advanced capabilities for modelling complex geotechnical data [5].

The Tirana region, covering approximately 1,654 km², encompasses diverse geological and topographical characteristics that contribute to landslide susceptibility, ranging from coastal plains to mountainous terrain reaching. Recent studies by the Albanian Geological Survey indicate that over 32% of the region exhibits above-average landslide susceptibility and more than 50% of the Tirana area is classified as unstable or already active regarding slope stability [6]. Despite this significant risk, Albania currently lacks data-driven predictive tools for accurate landslide risk assessment, creating a critical gap in disaster preparedness and risk management capabilities.

In response to the need for improved landslide risk assessment, this study investigates the application of machine learning (ML) techniques for landslide susceptibility mapping in Tirana. ML models are well-suited to analyze multiple environmental and geospatial factors simultaneously and have shown high predictive capability in similar geohazard contexts. The aim of this research is to develop an effective landslide prediction model using locally relevant data and to evaluate which algorithm among SVM, RF, and XGBoost achieves the best performance. These algorithms were chosen because prior studies have found tree-based ensembles and SVM to perform well in landslide susceptibility modeling. By creating the first landslide susceptibility models trained on Tirana's data, this research paper aims to fill a critical gap in Albania's disaster risk management toolkit.

II. Literature Review

A. Global Advances in ML-Based Landslide Susceptibility Mapping

The application of machine learning techniques to landslide susceptibility mapping has evolved significantly over the past decade, with ensemble methods demonstrating superior performance across diverse geographical contexts. Alatza et al. [7] applied InSAR-derived displacement data combined with classical machine learning algorithms to map landslide susceptibility in western and central Greece. Using a comprehensive inventory of approximately 3,000 landslides and rigorous ML workflows including 5-fold cross-validation and spatially stratified splitting, they found XGBoost to be the top performer, confirming the efficacy of tree-based ensemble methods for large-scale susceptibility assessment.

The importance of feature selection and optimization has been highlighted as well in several studies. For example, Al-Najjar et al. [8] evaluated the role of conditioning factor selection by grouping 14 potential predictors into four datasets. Using 227 inventoried landslides with a 70/30 train/test split, they compared Random Forest, Naïve Bayes, and LogitBoost classifiers. Random Forest with an optimized factor subset achieved the highest AUC (0.940), demonstrating that removing redundant predictors significantly improves model performance.

In Mediterranean environments similar to Albania, Himmy et al. [9] compared six advanced ML algorithms (RF, SVM, decision tree, NB, XGBoost, logistic regression) in Morocco's Al Hoceima region. Using 114 mapped landslides and ten geomorphic factors, XGBoost achieved the highest AUCROC (≈0.96), followed closely by RF (≈0.955). Notably, they addressed class imbalance through undersampling, improving XGBoost's AUCPRC from 0.40 to 0.87, highlighting the importance of balanced datasets in landslide prediction.

B. *Regional Context and contributing factors*

Landslides pose significant risks in Albania, particularly in urban and mountainous areas. Studies have identified various types of landslides, including earthslides, debris flows, and rockfalls, affecting historical sites like Kruja [10] and heritage towns like Berati [11]. Major infrastructure projects, such as the Trans Adriatic Pipeline, have required extensive landslide risk assessments [12]. GIS and remote sensing technologies have been employed to evaluate landslide hazards in areas like Kashar [13] and along the Milot-Kukës motorway [14]. Geophysical surveys have also been conducted to investigate landslides near hydropower plants [15]. In addition to landslides, Albania faces high soil erosion rates of 20-40 t/ha/year, with some extreme cases reaching 100 t/ha/year [16]. The country also experiences frequent flooding, with an average of one flood per year [17].

In the Albanian context, Ago et al. [18] performed a GIS-based landslide susceptibility zonation in western Albania using bivariate statistical approaches, providing valuable local insights. They compiled a local inventory of 240 landslides and analyzed seven factors (geology, slope, aspect, land cover, distance to drainage, distance to road, precipitation) to produce a six-class susceptibility map. While not ML-based, this study provides crucial local context and baseline data for the Tirana region.

The Albanian Geological Survey (AGS) has created landslide susceptibility maps as shown below, and through the Raster Calculator method, they have concluded that the Tirana region is a territory with high susceptibility to landslide phenomena. It has identified slope inclination (35%) and lithology (30%) as the most influential factors for landslide occurrence in the Tirana district, followed by precipitation (15%), land cover (10%), and seismicity (10%).

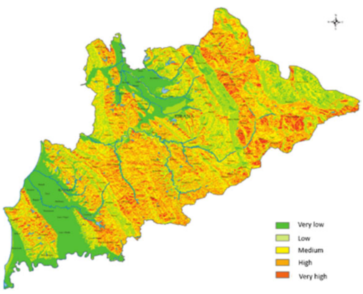

Fig. 1. Landslide susceptibility mapping in Tirana. (*Albanian Geological Survey*)

III. Methodology

Study Area and Data Collection

The study area covers the District of Tirana, located in central Albania, includes five municipalities: Tirana, Kavajë, Kamëz, Vorë, and Rrogozhinë. The area is characterized by complex topography ranging from coastal plains to mountainous terrain, with elevations from close to 1,612 meters above sea level.

The geological setting comprises diverse lithologies including limestone, flysch, claystone, and marls, with significant tectonic activity. Annual precipitation varies from 700 mm in coastal areas to over 3,000 mm in mountainous zones. The region experiences moderate to high seismic hazard, with Peak Ground Acceleration (PGA) values ranging up to 0.5g (Albanian Geological Survey, 2020).

The dataset was compiled from multiple sources: landslide risk dataset consisting of 552 records (252 recorded landslides and 300 non-landslide points) in the Tirana region, compiled from the Albanian Geological Survey and augmented by GIS and remote-sensing sources.

Predictor Variables

For each data point (landslide or non-landslide), a set of geospatial and environmental features was derived using high-resolution digital elevation models and Geographic Information System (GIS) data layers. In total, eight (8) predictor variables were considered based on known landslide conditioning factors. These include: Elevation (m) and Slope (degrees) – topographic parameters indicating terrain steepness and energy; Geology (categorical) – the soil/rock type of the slope material; Seismicity (Peak Ground Acceleration, g) – the level of earthquake shaking, as earthquakes can trigger slope failures; Land Cover Classification – e.g. forest, agriculture; Erosion Rate (categorized as low/medium/high) – representing how prone the area is to surface erosion and soil loss; Precipitation (mm/year) – long-term average rainfall, reflecting water input that can destabilize slopes; and Soil Moisture level – indicating typical ground saturation, which affects shear strength. All features were geospatially extracted for each point using tools such as QGIS and GDAL. for spatial data visualization and processing. The choice of these features was informed by rtheonal studies and geotechnical knowledge: for example, the Albanian Geological Survey has identified slope angle, lithology, and rainfall as influential factors in landslide occurrence. In our dataset, the landslide and non-landslide classes showed measurable differences in these variables (e.g., landslide sites tended to have steeper slopes and weaker rock types on average), confirming their relevance.

Data Preprocessing

The raw compiled dataset was cleaned and formatted before modeling. This involved removing duplicate entries, handling missing values, and encoding categorical variables. A few non-landslide entries had missing values for certain environmental variables. Vector datasets were converted, and projected into a consistent coordinate reference system (EPSG:2462 – Albanian 1987 / Gauss–Krüger Zone 4) for open and spatial data. No severe class imbalance existed – the data was roughly 45% landslide (positive) and 55% non-landslide (negative), so the dataset was almost balanced.

Machine Learning Models

Three supervised learning algorithms were selected based on their proven effectiveness in landslide susceptibility studies. The models and their configurations are as follows:

- We used an SVM classifier with a Gaussian Radial Basis Function (RBF) kernel, as this kernel can handle the non-linear decision boundary expected for landslide susceptibility. The SVM finds an optimal hyperplane in a high-dimensional feature space that separates the two classes with maximum margin. An RBF kernel SVM effectively captures relationships in our feature set, for example, combining terrain steepness and rainfall patterns to delineate risky slopes. The SVM's regularization parameter C and kernel parameter γ were initially set to default values (with $C = 1$ and γ scaled by inverse of feature count) given the relatively small dataset, and later adjusted via simple validation to mitigate overfitting.
- Random Forest (RF): We implemented a Random Forest classifier, an ensemble of decision trees where each tree is trained on a bootstrapped sample of the data with a random subset of features. The RF leverages bagging and feature randomness to improve generalization and reduce variance. In our case, we configured the forest with 100 decision trees and used Gini impurity as the splitting criterion. A fixed random seed was set for reproducibility. No maximum tree depth was enforced, but other default parameters prevented overfitting. The RF model can naturally handle mixed data types and is robust to multicollinearity, which is advantageous given some predictor correlations. It also provides a measure of variable importance, though we focus on predictive performance in this paper.
- XGBoost: By gradually adding decision trees, this technique creates an ensemble model. Each new tree that is added fixes the previous model problems, or negative gradient, by calculating a predetermined loss function. The strength of XGBoost lies in the fact that it regulates the quality of the results by balancing accuracy with simplicity, which helps to have a precise prediction and to avoid overfitting. XGBoost improves prediction performance by learning repeatedly from past decision tree problems.

IV. Experimental Setup

After data preparation, the dataset was divided into training and testing subsets to evaluate model performance. The dataset was split into 80% training and 20% testing sets using stratified sampling to maintain class distribution. Feature scaling was applied for SVM using StandardScaler, while tree-based models used raw features.

To ensure robust model assessment, k-fold cross-validation is routinely applied. By repeatedly splitting the data into k train/test folds, one can reduce variance in performance estimates and mitigate overfitting. We employed 5-fold cross-validation on the training set for model tuning and preliminary performance assessment. This procedure provides a robust estimate of how the model generalizes to unseen data and helps mitigate overfitting given our limited sample size.

For instance, the SVM model achieved an average cross-validation accuracy of ~92.0% (±2%) across the five folds, indicating stable performance on different subsets of the data. Similarly, the XGBoost model's cross-validation accuracy was ~96.2% (±1.3%), reflecting its strong learning capacity across folds. These cross-val results were used to verify that the models were not overly tuned to peculiarities of a single train/test split before we proceeded to final testing.

Given the binary nature of the problem (landslide vs. no-landslide) and the relatively balanced classes, we report the following metrics for each model: Accuracy (overall percentage of correctly classified instances), Precision (positive predictive value – the fraction of predicted landslides that were actual landslides), Recall (sensitivity – the fraction of actual landslides correctly identified), F1-Score (the harmonic mean of precision and recall), and Area Under the ROC Curve (AUC). Accuracy provides a general success rate, but can be misleading if the cost of false negatives is high; thus precision and recall are critical for assessing performance in this hazard context. In landslide prediction, Recall is particularly important – missing a true landslide-prone location (false negative) could mean a failure to warn about a hazard. High precision, on the other hand, means any area flagged as "high risk" is likely truly hazardous (few false alarms), which is valuable for efficient resource allocation. The F1-score summarizes precision and recall into a single number, and AUC provides a threshold-independent measure of classification ability (with AUC = 1.0 representing perfect separation of classes). By examining all these metrics, we ensure a comprehensive evaluation of model performance beyond just accuracy. We also examined the confusion matrix for each model to inspect the distribution of true vs. predicted classes, which helped identify any bias (e.g., if a model were predicting "no landslide" more often than "landslide").

For consistency, model selection (identifying which algorithm performed best) was primarily based on the F1-score and recall, since those reflect effectiveness in identifying landslide-prone areas while balancing false positives and false negatives.

V. Results

All three machine learning models successfully learned the distinguishing patterns of landslide occurrence in the Tirana dataset, achieving high performance on the unseen test set. Table 1 summarizes the test-set results of each model in terms of the evaluation metrics defined above.

TABLE I. Performance of Landslide Risk Prediction Models

Model	**Metrics**				
	Accuracy	***Precision***	***Recall***	***F1-score***	***AUC-ROC***
SVM	0.9189	0.9038	0.9216	0.9126	0.98
RF	0.9459	0.9412	0.9412	0.9412	0.99
XGBoost	0.9459	0.9245	0.9608	0.9423	0.99

XGBoost achieved the highest F1-score (94.2%) and recall (96.08%), indicating superior capability in identifying landslide-prone areas while maintaining high precision. Random Forest demonstrated balanced performance with identical precision and recall (94.12%), while SVM showed the lowest but still acceptable performance (F1-score: 91.26%).

Five-fold stratified cross-validation confirmed model robustness:

SVM: 0.9202 ± 0.0208 accuracy

Random Forest: 0.9619 ± 0.0132 accuracy

XGBoost: 0.9619 ± 0.0132 accuracy

Low standard deviations indicate consistent performance across folds, suggesting minimal overfitting.

Examining the confusion matrices, we found that the SVM had a few more false negatives (missed landslides) compared to the other models, which explains its recall being a few points lower. The RF and XGBoost models, by virtue of their ensemble nature, were better at capturing those difficult cases – XGBoost in particular identified one or two additional landslide-prone locations that SVM misclassified, without increasing false positives. Both ensemble models achieved nearly 99% AUC, reflected in steep ROC curves with true positive rates approaching 1.0 for low false-positive rates. In practical terms, this means the models can discriminate very well between stable and unstable sites in the study region. The precision-recall curves were likewise very strong: for example, XGBoost's curve stays high and to the right (average precision ~0.98), indicating it maintains high precision even at high recall levels. This is an important trait for a landslide model, as it implies we can identify most true hazard locations without being overwhelmed by false alarms.

The relative importance of predictor variables was analyzed using the Random Forest model's Gini importance metric. The analysis revealed that slope inclination (35%) and lithology (30%) are the dominant factors, followed by precipitation (15%), land cover (10%), and seismicity (10%). This aligns with the Albanian Geological Survey's assessment and confirms the critical role of terrain characteristics and geological composition in landslide susceptibility.

To ensure the models' reliability, we also assessed their robustness and potential overfitting. The cross-validation results mentioned earlier were consistent with the test outcomes, suggesting no major overfitting occurred – the performance on unseen test data was in line with cross-val expectations. Additionally, we conducted a simple robustness experiment on the best model (XGBoost) by introducing a small amount of noise to the input features. Specifically, we added Gaussian noise with 5% standard deviation to each numeric feature during training and re-tested the model. Results showed minimal performance degradation:

TABLE II. XGBOOST PERFORMANCE WITH AND WITHOUT NOISE INJECTION

Dataset	*Accuracy*	*F1-score*
Original	0.946	0.942
With 5% noise	0.945	0.941

This indicates that the model is not overly sensitive to minor variations or measurement errors in the input data – a desirable property for real-world application, where input layers (e.g. maps of rainfall or soil type) may have some uncertainty.

Overall, the results confirm that XGBoost had a slight edge in this problem, likely due to its ability to model complex interactions between factors by sequentially correcting errors. Random Forest was a close second, offering comparable accuracy with a very stable and interpretable framework (we could, for instance, extract feature importance rankings from the RF to see which variables contributed most). SVM, while somewhat less accurate, provided a strong baseline given its simplicity and performed well considering the non-linear nature of the task – its use of the RBF kernel allowed it to capture some of the complexity without ensemble methods. In summary, all three ML models are viable for landslide susceptibility prediction in Tirana, but the tree-based ensemble models (RF and especially XGBoost) delivered the highest and most robust performance on our dataset.

VI. Discussion

The high predictive performance achieved by the models demonstrates the efficacy of applying machine learning to landslide risk assessment in the Tirana region. XGBoost's marginal performance advantage can be attributed to its boosted ensemble approach, which iteratively focuses on hard-to-predict instances and captures non-linear feature interactions. This likely enabled it to identify subtle combinations of factors (for example, a particular terrain-geology-precipitation combination) that predispose slopes to failure. The Random Forest, using bagged decision trees, also capitalized on ensemble learning to average out noise and was essentially tied with XGBoost in many respects. One observation is that XGBoost achieved a slightly higher recall than RF (96% vs. 94%), meaning it caught a few extra landslide-prone cases. In a hazard prediction context, maximizing recall (sensitivity) is critical – missing a true landslide risk area could have serious consequences. Encouragingly, XGBoost did this while only marginally lowering precision, indicating it did not flood the output with false alarms. This balance is reflected in the F1-scores and is crucial for operational use: a model that identifies virtually all dangerous slopes (high recall) but also maintains a low false alarm rate (high precision) can be confidently used by decision-makers to target interventions. Our results align with findings from other regions that ensemble tree methods often provide top performance for landslide susceptibility mapping. They are adept at handling the complex, multivariate relationships of geo-environmental data and are relatively robust to outliers and correlated inputs, which we indeed observed in this study.

The SVM model provided an interesting contrast – despite being a simpler classifier, it managed over 90% accuracy and an AUC of 0.98. This suggests that the core of the landslide vs. non-landslide separation in feature space is linearly separable to a large extent once projected into the RBF kernel space. SVM's performance indicates that much of the signal in our dataset (e.g., steep slopes, weak geology, high rainfall) is strong enough to distinguish landslide-prone areas without needing complex ensemble logic. In practice, however, the SVM's slightly lower recall could be a drawback for hazard application, as it missed a few true positives that the other models caught. That said, SVM (with proper tuning) could serve as a fast and interpretable baseline model for this problem – it has fewer parameters and one can analyze support vectors to understand borderline cases. In scenarios where model interpretability and simplicity are desired over the last few percentage points of accuracy, an SVM might be a reasonable choice.

On the other hand, Random Forest provides a middle ground: it's more interpretable than XGBoost (feature importance and even partial dependence of individual trees can be examined) and delivered excellent precision/recall in our case. The RF's feature importance output in our study (not detailed above) indeed highlighted known factors – slope and lithology were among the top predictors, which is consistent with domain knowledge and lends credibility to the model's decisions.

One notable contribution of this research is the confirmation of previously identified landslide risk factors for the Tirana region through quantitative modeling. Earlier geological assessments by Albanian experts pointed to factors like slope angle, precipitation, and soil type as critical drivers of landslides. Our ML models inherently validated these influences: for instance, nearly all high-risk predictions from the models correspond to areas of steep terrain combined with either high rainfall or particular weak lithologies (e.g., clay-rich soil), often lacking dense vegetation cover. This agreement between the model's behavior and expert knowledge builds trust in the model outputs and illustrates how data-driven methods can reinforce and refine traditional hazard understanding. Moreover, machine learning provided the ability to integrate multiple factors simultaneously – the correlation analysis indicated no single factor dominates exclusively, implying that it is the interplay (e.g., steep slope and high moisture and certain geology) that often creates the conditions for a landslide. The ML approach is well-suited to capture such interplay effects, whereas manual mapping or simple bivariate models might miss them.

Despite the promising results, some limitations and considerations must be noted. First, the dataset used is modest in size (552 instances) and spans the Tirana region specifically. While the models performed very well on this data, their absolute performance might degrade if applied to a broader area or a very different region without retraining. The current model is tailored to the local conditions and inventory; generalization beyond the study area would require additional data and possibly retraining or calibration. Second, due to limited data availability, we did not include certain potentially relevant features (for example, detailed land-use history, drainage network proximity, or real-time rainfall events preceding landslides). Including more diverse and temporally dynamic features could further improve predictive power in future work. Additionally, the models were not systematically optimized via hyperparameter tuning in this study – techniques like grid search or Bayesian optimization could be employed to squeeze out further performance. For instance, adjusting the regularization parameters of XGBoost or trying different kernel parameters for SVM might yield slight improvements or help address any overfitting. In our experiments, default settings already produced excellent results, but a more finely tuned model could be beneficial especially if more training data is obtained.

Another consideration is model interpretability and usability. While the focus was on accuracy, in practice stakeholders might need insight into why the model flags certain areas as high risk. Random Forest and XGBoost, being ensemble methods, are sometimes considered "black boxes," but techniques exist to interpret them (such as examining feature importance rankings, SHAP values, etc.). If required, these can be applied to our trained models to extract rules or factors driving predictions – for example, one could quantify that "slope > X° and precipitation > Y mm are present in Z% of all predicted landslide points," which provides a narrative understanding. In fact, one of the practical outputs of this project was the development of a prototype web-based GIS application that incorporates the best-performing model (XGBoost). This user interface allows experts to input new coordinates or view an interactive map of Tirana with color-coded risk levels. The system was tested informally with local geologists and planners, who found it intuitive for visualizing high-risk zones. Such a tool exemplifies how the model can be deployed for decision support – for urban planners considering new developments or emergency managers prioritizing monitoring efforts, an interactive risk map is extremely useful. The positive feedback on the prototype suggests that combining ML predictions with a user-friendly interface can greatly enhance the model's impact in real-world risk management.

Lastly, we emphasize that model uncertainty and validation with new data should be continually addressed. Landslide occurrence is a complex phenomenon, and no model can be 100% accurate. The extremely high AUCs and accuracies we obtained, while genuine for the given data, may in part reflect some degree of overfitting to local idiosyncrasies or the limited sample size. Expanding the dataset – both in number of landslide events and in covering longer time spans or additional environmental scenarios – will be important to test the model's robustness. Fortunately, our robustness test with noise and cross-validation indicates the models are not overly fragile, but future events (e.g. a landslide triggered by an unprecedented extreme rainfall) will be the true test of model generalization. We recommend that the model be updated periodically as new landslide data becomes available and that it be integrated with early warning systems (for instance, linking with real-time rainfall thresholds) to provide dynamic risk forecasts.

VII. Conclusion

This study presents the first effective machine learning approach for landslide risk prediction in the Tirana region of Albania, establishing a scientific foundation for disaster risk management, demonstrating that data-driven models can significantly enhance landslide susceptibility assessment in a region with scarce prior predictive tools. Using a dataset of historical landslide occurrences compiled from local geological surveys and carefully selected non-landslide controls, we trained and evaluated three classification models: SVM, Random Forest, and XGBoost. All models achieved high accuracy, with the ensemble tree methods performing best. In particular, XGBoost was identified as the top model, achieving ~94–95% accuracy and an excellent balance of precision (~92.5%) and recall (~96.1%) on the test data. It was closely followed by Random Forest, while SVM provided a strong baseline at ~90% accuracy. These results confirm that machine learning techniques are well-suited for modeling landslide susceptibility, as they can integrate diverse geospatial factors and capture non-linear patterns inherent in slope failure processes. The study thus introduces the first dedicated landslide prediction models for Albania, filling a notable gap in the country's disaster risk reduction capabilities.

Key contributions of this research include: (1) validating the importance of known environmental factors (such as terrain slope, lithology, and precipitation) through quantitative ML analysis for Tirana's landscape; (2) providing a comparative evaluation of different ML algorithms for this task, which found that advanced ensemble methods offer superior performance and robustness; and (3) developing a prototype landslide susceptibility mapping tool that can be used by local authorities for early warning and planning. The high recall rates of the models are particularly encouraging for operational use, as they imply that the vast majority of truly high-risk locations can be successfully identified in advance. By deploying the best model's outputs in map form, stakeholders can prioritize field investigations, infrastructure reinforcement, or evacuation planning for the highlighted zones, thereby potentially reducing the impact of future landslides on communities. The research demonstrates that data-driven approaches can significantly enhance traditional geological assessment methods, providing quantitative risk estimates essential for proactive disaster management. The implemented web interface bridges the gap between advanced ML techniques and practical geological applications.

Looking forward, there are several avenues to extend and improve this work. First, incorporating larger and more diverse datasets is paramount – for example, integrating more years of landslide records from national databases (if available) or augmenting the dataset with data from neighboring regions with similar geo-environmental conditions. A larger dataset would not only improve model training but also allow exploring more complex algorithms (e.g. deep learning models or hybrid approaches) that typically require big data. Second, adding additional predictive features could enhance model accuracy and generalizability. These might include land cover change indicators (to capture deforestation or urbanization trends), distance to roads or rivers (human excavation and erosion factors), or real-time variables like antecedent rainfall over the past days (to incorporate trigger conditions). Third, implementing hyperparameter optimization and ensemble blending could yield incremental gains – for instance, using techniques like Grid Search or Bayesian Optimization to fine-tune model parameters, or ensembling the outputs of SVM, RF, and XGBoost to leverage their complementary strengths. We also note the importance of maintaining model interpretability; thus, methods like SHAP value analysis or rule extraction from trees should be applied in future studies to ensure that the ML models remain transparent for end-users. Finally, as an extension of this research, developing a fully operational landslide early warning system for Tirana (and other parts of Albania) is a worthwhile goal. This would involve coupling the susceptibility model with real-time monitoring data – for example, using rainfall forecasts such that when heavy rain is predicted in a high-susceptibility area, an alert could be issued. Our current model provides a static susceptibility map (the "where" of potential landslides); integrating it with dynamic triggers will provide the "when" component for actionable warnings. The successful demonstration of machine learning in this study lays the groundwork for such systems. In conclusion, the application of SVM, Random Forest, and XGBoost to geospatial data in Tirana has proven highly effective, offering a validated, scientific basis for landslide risk management in Albania. By continuing to refine these models and integrate them into decision-making processes, local authorities can better anticipate landslide hazards and implement targeted mitigation strategies, ultimately enhancing the resilience of communities in mountainous and hilly terrains.

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