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GeoPulse: A Low-Cost Machine Learning Rockfall Prediction System

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Abstract—Rockfalls cause significant risks which pose threats to infrastructure and transport systems and human lives in the mountainous and mining regions. The study proposes a data informed rockfall risk forecast system that relies on weather conditions and precipitation patterns to establish the risks before they occur. The study formed an organized dataset that comprised of rains intensity measures and slope angle data and ground vibration data and temperature recordings as it created other time-varying characteristics that would assist in witnessing gradual slope destabilization impacts. Two supervised machine learning models were utilized in the research and they comprised of Logistic Regression and the Random Forest to undertake predictive analysis. The outcomes of the experimental evaluation were excellent as the Logistic Regression was very high and the random forest produced a very high accuracy of 97% and the ROC-AUC of 0.9841 that exhibited a very high level of discrimination. The confusion matrix test revealed that the system had a great true positive detection at minimal false negative outcomes that indicated that the system can be useful in safety-related scenarios. The study found that two main factors that is how much rain had fallen and how steep the slopes were, played the biggest role in triggering rockfall events. To help manage this risk the system calculated probabilities and grouped them into three categories: low, medium, and high. These categories were then used to generate early warnings, giving people the chance to take action before a rockfall occurred. The proposed framework which uses low-cost sensors to detect rockfalls establishes a new method for rockfall prediction which moves from static susceptibility evaluation to dynamic real-time risk assessment that applies to resource-limited settings.

Keywords —FRockfall prediction, Early warning system, Machine learning, Random Forest, Logistic Regression, Temporal feature engineering, Rainfall accumulation, Slope stability, ROC–AUC analysis, Environmental hazard modeling.

I. INTRODUCTION

Rockfall occurrences are among the most common and dangerous types of gravitational mass movements in mountainous terrain. Unlike other landslide processes, rockfalls are sudden events with high kinetic energy, and their occurrence depends on a combination of geological factors, such as slope morphology and geology, and climatic factors, such as rainfall, as well as dynamic factors, such as seismic and human-induced vibrations. This complex dependence makes it difficult to predict rockfall occurrence and path using traditional geomorphological assessment approaches [2].

Traditional rockfall hazard assessment is a field-based assessment technique that uses expert judgment, susceptibility mapping, and deterministic physical models of block release and rockfall runout behavior based on assumed geology and slope conditions [1]. Machine learning algorithms have been created using regression based on the calculation of significant variables of rockfall hazard including run out distances and impact energies by use of slope geometry and photogrammetric measurements [3]. They are methods that are more predictable than statistical techniques used in conventional ways. Similarly, data-driven models have been made of the dynamics of rockfalls, which involve algorithm implementation, such as K nearest neighbors and neural networks, to analyze trajectory behavior at different starting conditions and give more insights into rockfall processes.

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Hybrid machine learning models that integrate ensemble models such as XGBoost and LightGBM with logistic regression have been shown to possess immense potential in enhancing the accuracy of rockfall susceptibility mapping. Apart from numerical models and machine learning models, advanced rockfall detection systems that apply deep learning for intelligent rockfall identification on mountain roads have been proposed, which highlights the increasing trend towards real-time monitoring and early warning systems integration.

High-resolution remote sensing data, including LiDAR point cloud data, have further enhanced the ability to evaluate slope conditions and update trajectory prediction models with high-resolution three-dimensional structural data. Apart from numerical models, susceptibility and risk evaluation studies carried out in various geographical regions, including Italy and Türkiye, indicate the general applicability of data-driven rockfall analysis approaches for regional hazard planning and decision support. In addition to rockfall-related literature, research on machine learning in early warning systems for geotechnical hazards has underscored the value of combining various environmental factors in predictive models that can be applied generally to slope instability events. In spite of these developments, there are still issues in designing predictive models that can be used for real-time forecasting, dealing with data sparsity, and being interpretable and easily applicable in developing environments [4].

II. BLOCK DIAGRAM

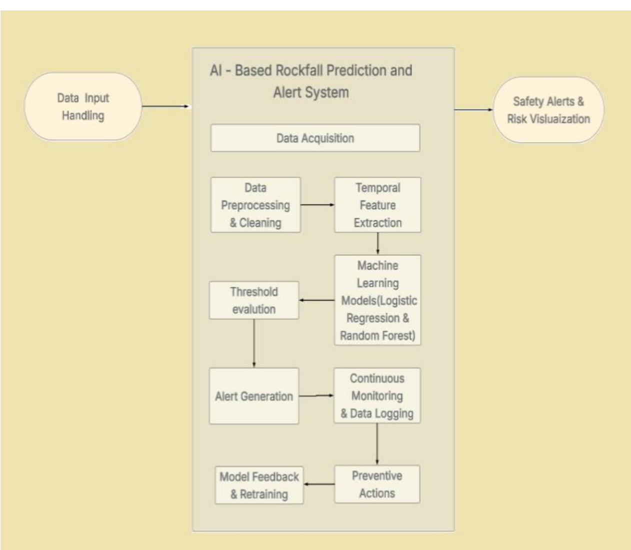

Fig.1 Rockfall Prediction and Alert System processing pipeline block diagram.

Fig.1 shows an AI-based system that processes input data through preprocessing, feature extraction, and machine learning models to predict rockfall risks.

Based on thresholds, it generates alerts, enables preventive actions, and continuously improves through monitoring and model retraining.

III. LITERATURE REVIEW

Rockfall risks are a significant safety issue in the underground and open-pit mining conditions, which commonly results in loss of lives, damaged infrastructure, and delays in operations. In order to mitigate these risks, a number of studies have been performed to learn the processes of rockfalls as well as the concept of developing prediction and early warning techniques using geological, statistical, and artificial intelligence-based methods. Doredla and others conducted a study on the hazards of rockfall in underground mines and have come up with a predictive model, which relies on the geological factors, environmental factors and disturbances as a result of mining. Their work placed an emphasis on the role of rock mass properties and redistribution of stress on the occurrence of rockfalls. Even though the model enhances comprehension of hazards, it heavily depends on preset parameters and is not able to incorporate sensors in time and automatic systems to generate warnings, which can restrict its flexibility to dynamic mining settings. Rockfall-prone regions have been identified using spatial susceptibility analysis. Tosevski et al. (2021) suggested a bivariate susceptibility modeling methodology in the seed cell concept that determined the possible rockfall source areas depending on geological and terrain parameters [12]. Although it is effective in space hazard mapping, the method is more devoted to analyze the static susceptibility and fails to provide a temporal projection and operational deployment in real time. Modeling of complex rockfall behavior has attracted interest in data-based methods. The study of Ghahramanieisalou and Sattarvand (2024, 2025) was provided on the basis of the laboratory scale, where machine learning methods were used to forecast the dynamics of rockfalls. Their efforts showed that data-based models could perform more effectively than physics-based models in telling the patterns of rockfall motion [4]. Yet, they were carried out in the controlled experimental setting and were not supported by experimentation on real-world mining data and also were not combined with the real-time monitoring and alert systems.

Field-scale rockfall hazard prediction has also been performed by the use of machine learning models. The authors suggested a machine learning model based on regression to predict the hazards of rockfalls in open-pit mines (Senanayake et al., 2024) [3]. They have found that machine learning models are accurate enough to manage non-linear links between geological and environmental parameters. However, the model was primarily concerned with the level of prediction accuracy but not with feature extraction of time, constant surveillance, and real-time warning systems. The latest studies have discussed the use of advanced sensing and deep-learning methods to detect rockfalls. Farmakis et al. proposed a LiDAR-based rockfall detection system that is based on deep learning and allows high detection accuracy and fine mapping of unstable rock masses [13]. The activities of LiDAR can be costly, computationally demanding, and not designed to predict continuously in real-time, especially in underground mines despite its effectiveness. Risk management perspective has also been examined to artificial intelligence. Chanut et al. summarized the use of AI models in rockfall risk management and emphasized its benefits as a decision support tool and hazard evaluation [16]. Nonetheless, the paper failed to suggest a common model that incorporates real-time data capture, temporal prediction, and automatic detection of alerts.

Abaker et al. (2023) suggested a framework of early warn of rockfalls using deep learning and IoT to combine sensor information and deep learning models [15]. Nevertheless, deep learning models are data-intensive and computationally expensive and the inability to offer interpretability introduces issues when using these models in safety-critical mining tasks. Video-based methods of rockfall detection have been studied. Wang et al. put forward a video-stream-based rockfall motion detection and tracking system which can detect rockfall motion by visual means. Although in a controlled environment they are effective, they are so sensitive to lighting and visibility and the placement of the cameras that they can hardly be relied upon to work effectively in the underground mining environment. Based on the literature reviewed, it is clear that the current literature is devoted to separate elements of rockfall management, including spatial susceptibility mapping, laboratory-level modeling, single machine learning prediction, or post-event detection. The majority of methods do not have an embedded system that integrates real-time multi-source data collection, temporal features engineering, probabilistic risk rating, and automatic alerting. Moreover, there has been a lack of particular focus on the interpretability of models and re-training on a real-time basis, which are needed by the safety-oriented mining systems.

IV. PROPOSED METHODOLOGY

The suggested methodology is an AI-based Rockfall Prediction and Alert System that is to continuously monitor the geotechnical and environmental conditions, predict the possible occurrence of rockfalls, and produce early warnings to improve the safety in the mining and mountain areas. The architecture of the system is in three stages: Input Layer, Processing System, Output Layer.

A. Data Input Handling

The input portion of the system receives and organizes the information to make an accurate decision, and this is where the proposed rockfall prediction and alert system will start. There are several geological, environmental as well as mechanical aspects that affect the phenomenon of rockfall and therefore, it is essential to consider data of various sources. To measure the slope stability, this layer captures the geotechnical parameters such as the surface roughness, the joint orientation, the rock mass properties as well as the slope angle. Since the environmental factors (temperature, humidity, rainfall intensity and cumulative precipitation) influence the rock strengths and fracture growth, these environmental factors are also collected. Further, the sensors installed are used to continuously measure dynamic values such as micro-seismic activity and ground vibration. These measurements give early warning of the movement of rocks, and the change of stresses within the rocks. To assist the system to understand what has happened in the past, past rockfall events are also provided. The data format and frequency is different as they are gathered in different sources. The input handling module ensures proper time synchronization, data structuring and data storage. This reliable data preparation enables the generation of timely alerts and accurate predictions of machine learning. Fig. 2 shows the general design of the rockfall prediction system.

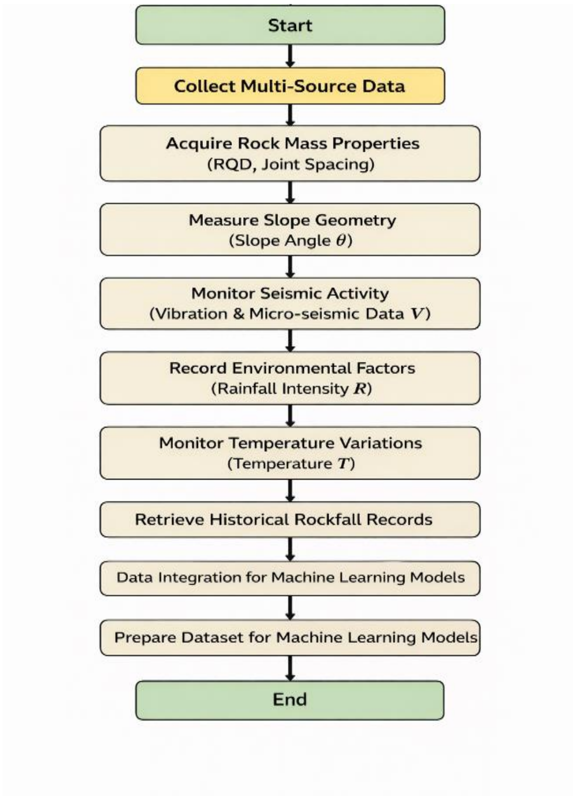

Fig.2 Rockfall Prediction Process Flowchart

B. Processing System

The most important part of the proposed rockfall prediction framework is the processing system that transforms the collected input data into meaningful predictions. It cleans and preprocesses data in order to deal with missing data, noise, and heterogeneous data. Time-dependent patterns related to rock movement and environmental changes are registered in such a way as to involve the perturbation of time, so temporal feature extraction is employed. The probability of a rockfall is then determined by processing the obtained features with machine learning models. The system eases the decision making process as it allows generation of alerts and preventive measures which are based on set thresholds.

1. Data Acquisition

The rockfall prediction structure has an aspect that does it all. This section examines the incoming information that is continuously flowing in and the information which we already possess such as sensors, geological surveys and weather monitoring systems. These sources supply us with a lot of information. We consider it as the one that evolves. In this manner we are able to cope with things that are going on. Possible future occurrences. We take this information. We wipe it off till it makes sense. We take out the parts fill in the missing parts and ensure all is consistent to enable us use it to foretell when rocks may fall. The temporal feature extraction is used to achieve variations and trends of slope behavior and environmental variations across the time. Lastly, machine learning models are utilized to process the refined data and predict the risk of rockfalls and aid in the generation of alerts on time.

$$D_t = \{x_t | t = 1,2,3,\ldots.\} \qquad (1)$$

Equation (1) represents a dataset or sequence D t comprising of elements x t defined by the parameter t as an integer, which begins with the value 1 and continues ad infinitum. In other words, D t denotes the collection of observations D x t at time steps D = 1, 2, 3,... t = 1, 2, 3,...

2. Data Preprocessing and Cleaning

Pre-processing and cleaning of the data is necessary to enhance the accuracy of the proposed rockfall prediction system and its reliability. Raw sensor data is usually full of noise, missing data and incongruence caused by environmental disturbances and sensor constraints. The stage involves missing data treatment, noise elimination and the normalization of all features to a standard scale. This creates a consistency in the processed data, which can be effectively used in the training and prediction of machine learning models.

Missing value handling

$$x_{missing} = 1/n \sum_{i=1}^{n} x_i \qquad (2)$$

Equation (2) is the mean imputation technique that is applied to address missing values of a dataset. The missing data value x{\|human|>The missing data value x{\|human|>The mean of the available data values xi is used to obtain the missing data value x.

Normalization (Min-Max Scaling)

$$x_{norm} = (x - x_{min})/(x_{max} - x_{min}) \qquad (3)$$

The normalization method used in the Min-Max is equation (3) and is used to normalize the actual data value x in the range 0-1. In this case, xmin and xmax represent the lowest and highest values of the data set respectively.

Noise Filtering

Outliers are removed using statistical thresholds or moving averages.

3. Temporal Feature Extraction

The time temporal feature extraction is important in the proposed system of rockfall prediction because rockfall is a time-dependent phenomenon. This step examines the changes in sensor readings with time in order to determine trends and abrupt variations that make an alarm with regard to slope instability. Sliding window methods or methods to obtain short term and long term temporal trends within continuous data streams are employed. These temporal features which are extracted help the model a lot in predicting the upcoming rockfalls with high accuracy.

$$F_t = \{ x_{t-\omega}, \ldots\ldots, x_t \} \quad (4)$$

The feature window or sliding time window in the time-series analysis is represented by equation (4). The sequence of the observations of xt-omega to xt is contained in the set Ft. This window stores the current values of the data in history that were recorded until time step tand, and is usually an input feature to a prediction model.

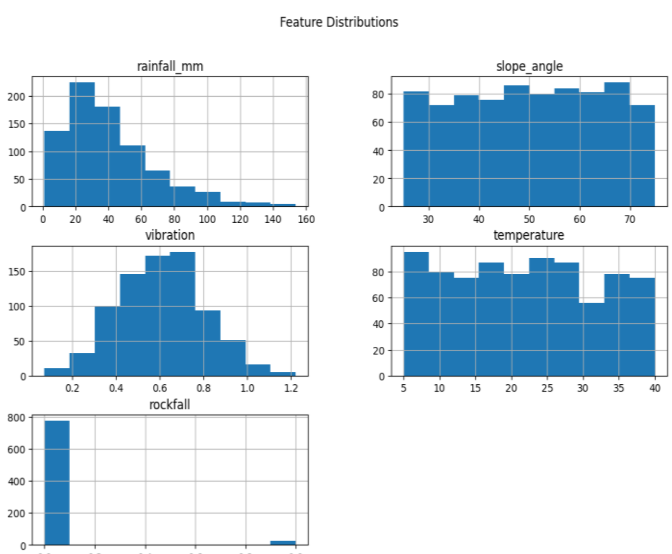

Fig.3 Feature Distributions

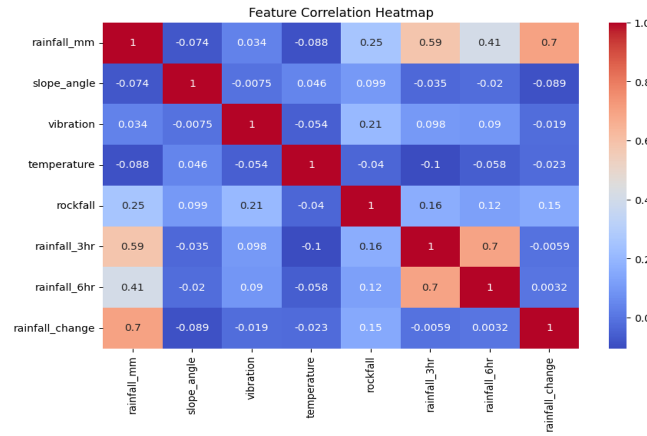

Fig 4. Feature Correlation Heatmap

The extracted features are depicted in the distribution in Fig. 3 and allow seeing how various input parameters change and affect the rockfall prediction model. Fig. 4 shows the associations between these characteristics in the form of a heatmap of correlation, which demonstrates the intensity of relationships between geological and environmental variables.

4. Machine Learning Prediction Models

The rockfall prediction section of the system examines the data we possess to determine the likelihood of occurrence of the rockfalls. This is where we use computer programs like Random Forest and Support Vector Machine to understand how different things, like the earth and the environment and how things move are connected. When we are dealing with information that changes over time we use something called Long Short-Term Memory networks to see how things are related to each other at times and how things are changing. The rockfall prediction models are trained using information from rockfall events and the things that happened before they occurred like the rockfall events and the input features that we have. Based on this learning, the system outputs a probability score indicating the level of rockfall risk.

$$\hat{y} = f(F_t;\theta) \quad (5)$$

Equation (5) represents the prediction function of the machine learning model. The predicted output yis generated by applying a function f(·)to the feature set Ftwith model parameters θ. The function frepresents the trained model that maps the input features to a predicted class.

Where:

$\hat{y} \in \{0,1\}$ (0 = Safe, 1= Rockfall risk)

Θ represents model parameters

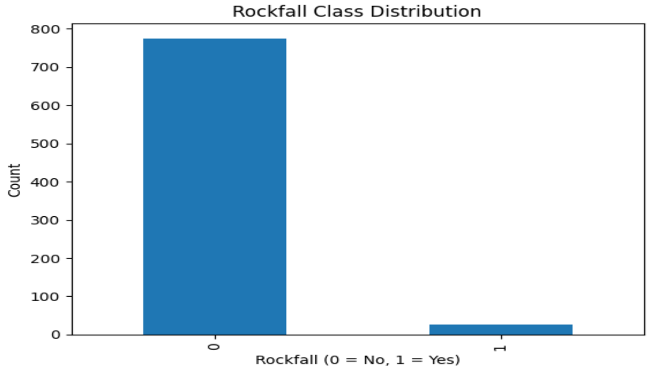

Fig 5. Rockfall Class Distribution

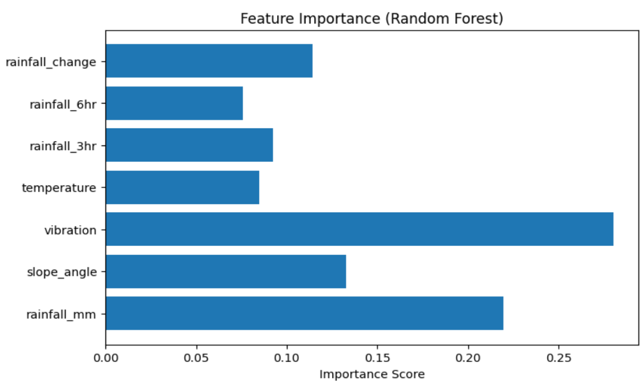

Fig 6. Feature Importance Score using Random Forest

The distribution of rockfall classes is presented in Fig. 5, showing the proportion of different categories in the dataset used for model training. Fig. 6 illustrates the feature importance scores obtained from the Random Forest model, highlighting the most influential parameters contributing to rockfall prediction.

5. Threshold Evaluation

Threshold evaluation is used to assess the severity of rockfall risk based on the probability output generated by the machine learning model. A predetermined threshold value is used to compare the predicted possibility with to consider the condition as a safe or risky condition. When this probability is above the threshold the system recognizes a high risk of rockfalls situation. The mechanism is used to minimize false alarms and to detect potentially dangerous conditions in time.

$$\text{Risk} = \begin{cases} \text{High}, & P(\text{rockfall}) >= \tau \\ \text{Low}, & P(\text{rockfall}) < \tau \end{cases} \quad (6)$$

Where τ is the predefined threshold (e.g., 0.7).

Equation (6) is the threshold based classification rule that is used to obtain the final prediction. The resultant probability p that the model generates is compared to a given threshold of T. When the probability is above the threshold or above, the output is considered as rockfall risk (1); otherwise, it is considered as safe (0).

6. Alert Generation

The generation of alerts is done when the forecasted risk of a rockfall is above the predetermined threshold value. At this phase, the system will provide real-time warnings at once to the relevant authorities and on-site personnel. Alerts may be provided in visual display, sounding alarm, or mobile messages, so that there is quick awareness. This communication allows timely taking of preventive measures before an incident of a possible rockfall occurs.

```
IF Risk ≥ Threshold
    Generate Alert
ELSE
    Continue Monitoring
```

7. Continuous Monitoring and Data Logging

A continuous monitoring and data logging is also an important aspect of the suggested rockfall prediction and warning system. At this phase, incoming sensor data and model predictions are constantly saved in organized database. This recorded data assists in providing real-time monitoring of the system and the analysis of post-event of a rockfall on a case-by-case basis. The performance of the models is also evaluated using the stored data and prediction errors or false alarms are also detected. Moreover, the data can be logged continuously, allowing periodic retraining of models which will provide a better performance and long-term reliability of the systems.

$$\text{Log} = \{D_t, \hat{y}_t\} \quad (7)$$

The prediction log as depicted in equation (7) has the input dataset Dtand the predicted output obtained at a given time, i.e. the predicted value of y t. The model predictions and the data are kept in this log at time step t to monitor, evaluate and later analyze them.

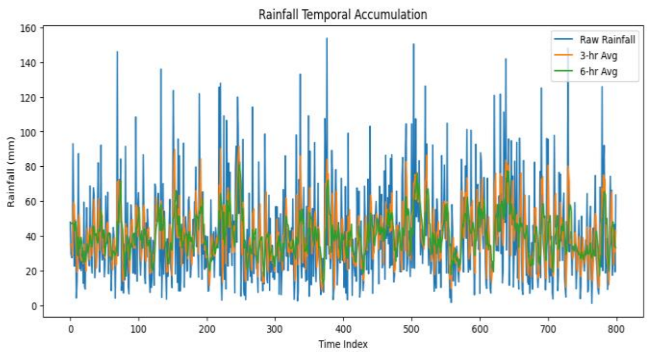

Fig 7. Rainfall Temporal Accumulation

8. Preventive Actions

The proposed rockfall forecasting and warning system should consist of continuous monitoring and recording. At this stage, a formal database is to be utilized and all incoming sensor data and the model predictions should be stored in this database in a continuous manner. This logged data can be used to conduct in-depth analysis of events that happened following a rockfall and to monitor the system in real-time. Moreover, the collected data is stored and used to evaluate the performance of the model and reveal false alarms or inaccurate predictions. Moreover, continuous data logging simplifies the frequent model retraining to ensure high accuracy and reliability of the system in the long run.

9. Model Feedback and Retraining

To maintain the effectiveness of the proposed rockfall prediction system in the long-term, retraining and the model feedback are necessary. Machine learning model is constantly improved by examining new sensor data obtained and confirmed rockfall events. This feedback mechanism allows changing the model parameters to adapt to the changing geological and environmental conditions. The system is able to increase its learning capacity gradually by introducing new patterns and correcting previous prediction errors. The retraining frequently reduces the missed detections and false alarms. The system remains precise, reliable and reconfigurable in case of long term rockfall surveillance and early warning.

$$\theta_{new} = \theta\_old + \Delta\theta \tag{8}$$

Equation (8) is the parameter update rule of the model learning or optimization procedure. The new parameter value, theta new, is determined by updating the old parameter value, theta old, with the update term, Delta theta. This is the update term which denotes the changing of the parameters used in training to enhance the prediction performance of the model.

C. Output Layer

The final stage in the proposed rockfall prediction and alert system is the output layer whereby the end users are informed of the results of the processing system in a useful and understandable way. This interface converts the complex machine learning predictions to interpretable safety information to field operators and decision-makers. One of the primary outputs is risk visualization that encompasses the graphical depiction of risks and their concentration in the regions prone to rockfall. Such maps would help authorities to prioritize safety measures and quickly pinpoint the areas that are at risk. What is more, the system provides probability scores, which, under varying circumstances, measures how likely it is that a rockfall will happen. These probabilities are further categorised in terms of warning level which includes Low, medium and High risk to facilitate easier interpretation. When a situation of high risk occurs, real time safety alerts are sent via visual dashboards, alarms or notification systems. The output layer is designed in such a way that it helps in immediate understanding and response. It enables preventive measures such as evacuation, access control, and slope control because the information is provided in a timely and accurate manner. In general, the output layer is needed to transform the findings of the analytical work into reasonable judgments on the level of safety and minimize the potential effects of rockfall risks. Fig. 8 represents the output of the proposed system in which the forecasts are transformed into risk maps, probability scores, and warning levels to help take up timely safety measures.

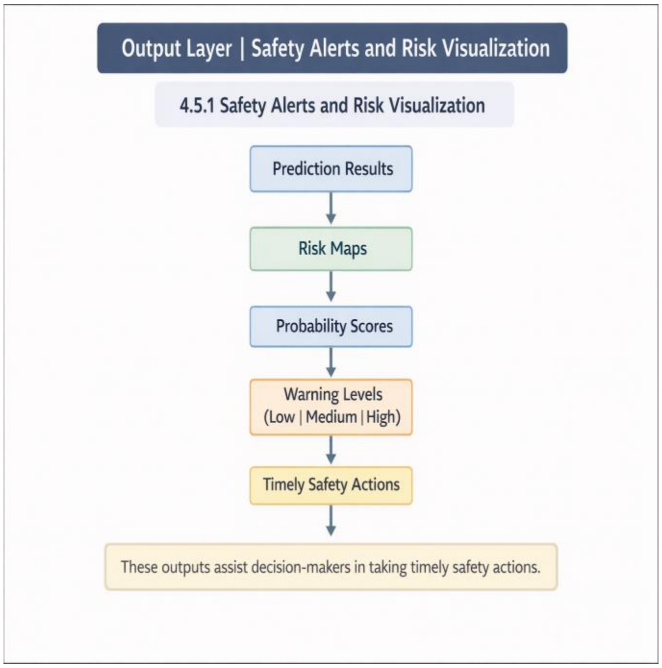

Fig 8. Output Layer (Safety Alerts and Risk Visualization)

V. RESULTS AND DISCUSSION

As explained above, the GeoPulse framework is a relatively inexpensive and efficient predictor of rockfall to enhance the early warning systems and enhance safety in mountainous and land slide prone regions. The proposed system will be based on different machine learning methods and data processing tools in a single integrated pipeline to examine and forecast possible rockfall incidents. It is also suggested to train the models with the help of different features such as the angle of the slope, the properties of soil, rainfall, the history of rockfall, and other characteristics to collect and process them with the proposed system. Data analysis can be done using a tool like Pandas and NumPy; which are Python-based and Scikit-learn can be used to apply machine learning algorithms like the Random Forest to classify and predict data. We can use libraries like Matplot and Seaborn to figure out the pattern and trends of the data presented. Accuracy, precision, recall, F1 score, and ROC-AUC are also used in the model to analyze the predictions of the model as to make sure the results derived are reliable. All in all, GeoPulse aims to deliver a simple to use and scalable rockfall prediction system that can aid authorities in taking preventative measures towards disaster reduction purposes.

Logistic Regression Accuracy: 0.97

Table 1. Classification Report of Random Forest

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0 (No Rockfall)	0.98	1.00	0.99	194
1 (Rockfall)	1.00	0.50	0.67	6
Accuracy	-	-	0.98	200
Macro Average	0.99	0.75	0.83	200
Weighted Average	0.99	0.98	0.98	200

The evaluation of a classification model with a classifier denoted as the Random Forest is provided in the table 1. It is also evident that the model is doing quite well as its accuracy is very high; it is at 0.985 or 98.5%. This means that the model has been successful in classifying most of the test data samples. Additionally, the precision for class 0 is 0.98, while for class 1, it is 1.00. This means that the model is making very few false positives. However, for class 1, the recall value is 0.50. This means that only half of the class 1 instances are correctly classified. The F1 score for Class 0 is 0.99, but for Class 1, it is 0.67. This indicates that the model is performing poorly in the minority class. It has been noted that in the given dataset, there are 194 examples in Class 0 and only 6 examples in Class 1. This has affected the ability of the model to detect the minority class. The ROC-AUC score is 0.984, which indicates that the model has high capability in distinguishing between two classes. Thus, it can be said that the Random Forest model has performed well with minor issues in detecting the minority class.

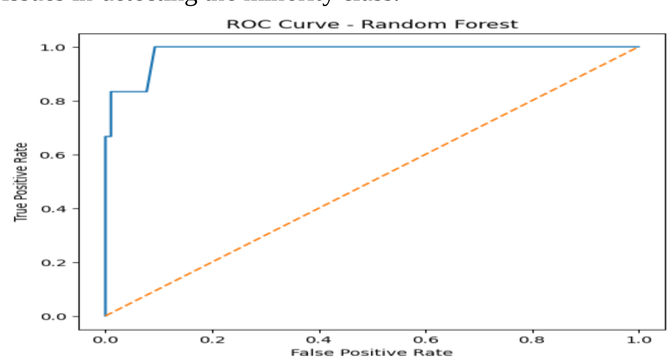

Fig 9. ROC Curve of Random Forest Model for Rockfall Prediction.

The above figure 9, shows the Receiver Operating Characteristic Curve (ROC Curve) of the Receiver Operating Characteristic (ROC) curve of the Random Forest model used in the GeoPulse rockfall prediction system. The ROC curve is

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a curve that plots the True Positive Rate and False Positive Rate for different thresholds of the classification model. The blue line indicates the performance of the Random Forest classifier, and the diagonal dashed line indicates the performance of a random classifier. Based on the figure, it is clear that the curve is well above the diagonal line and is moving towards the top left of the plot. This indicates that the model has a high ability to distinguish between rockfall and non-rockfall events. The higher the area under the ROC curve, the better the model performs. In this case, the model performs excellently, indicating that it can effectively identify potential rockfall risks. This shows that it can be used for disaster risk management.

Random Forest Accuracy: 0.985

Table 2. Predicted Rockfall Risk Levels by GeoPulse Model.

Sample ID	Risk Probability	Risk Level
1	0.000000	LOW
2	0.106667	LOW
3	0.000000	LOW
4	0.006667	LOW
5	0.000000	LOW

The above table 2, shows the predicted risk level for the rockfall scenario using the machine learning model GeoPulse. The figure indicates the probability values of all the samples for the particular scenario, and their corresponding risk level classification. The probability values vary from 0.000000 to 0.106667. Hence, the probability of occurrence of the rockfall event is very low. Therefore, all the samples are classified under the "Low" risk level classification.

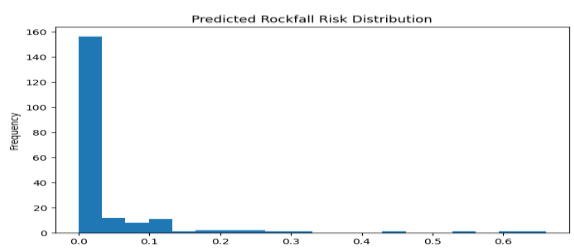

Fig 10. Predicted Rockfall Risk Probability Distribution using GeoPulse Model.

As can be seen from the figure 10, it can be observed that the figure represents the distribution of the predicted risk probability values for rockfall, which have been calculated by using a machine learning model named GeoPulse. The histogram in the figure above represents the distribution of the number of different risk probability values that have been calculated by the model. It has been observed that the majority of the values are concentrated around extremely low probability values approaching zero, which indicates that the majority of the areas have been identified as being at a lower probability of rockfall occurrence. It has also been observed that a few values are present at higher probability values, which indicates that the model has identified a few areas of risk and has identified the majority of the areas as safe.

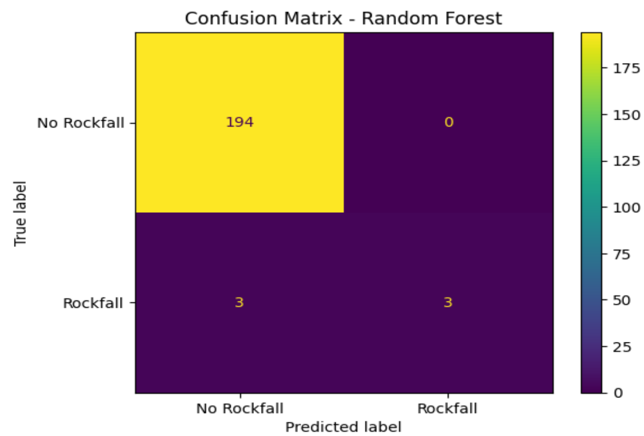

Fig 11. Confusion Matrix of Random Forest Model for Rockfall Prediction.

The above figure 11, indicates a confusion matrix of a model that used a Random Forest algorithm for a GeoPulse rockfall prediction system. The model compares the actual class labels and predicted class labels. According to the figure, 194 instances are correctly classified as "No Rockfall," and 3 instances are correctly classified as "Rockfall." However, 3 instances of rockfall are incorrectly classified as "No Rockfall." Additionally, there are no instances of false positives in the model, indicating that it does not wrongly predict instances of rockfall when they are not happening. The above figure indicates that the model is performing very well in classifying instances of non-rockfall and moderately in classifying instances of rockfall.

CONCLUSION

The research developed a rockfall prediction system that uses machine learning together with environmental sensors and rainwater prediction models to evaluate danger levels with accurate results. The framework achieved successful detection of rockfall occurrence through its integration of short-term rainfall accumulation data with rainfall change patterns, slope characteristics, vibration signals, and temperature conditions Logistic Regression produced a good baseline score, and with a great ROC-AUC of 0.9841, Random Forest was able to score 98.5% predictive accuracy, indicating that it is capable of modeling the nonlinear geohazard associations. The joint analysis of the visualization results and the feature importance studies attested the importance of hydrological loading and slope geometry as the determinant factors of rockfall initiation. The functionality of the system to offer early warning and decision-making support was enhanced by transforming prediction probabilities into categorical risks levels. The simulated data used in the current research gives an impression that the current research is applicable in the real-world environment, although it is not applicable since the method developed is what can be adopted by organizations to roll out their operations in the real-world environment.

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