ROCKNET : ADVANCING SEISMIC EVENT DETECTION

[1] **Murthy Mounika,** [2] **Dr. V. Uma Rani,** [3] **Dr. Sunitha Vanamala**

[1] Student, Department of Information Technology, University College of Engineering Science and Technology, JNTU Hyderabad.

[2] Professor Of CSE, Department of Information Technology, University College of Engineering Science and Technology, JNTU Hyderabad.

[3] Lecturer, Department of Computer Science, TSWRDCW, Warangal East, Warangal, Telangana, India

Abstract: Seismological data is crucial for assessing slope failure hazards promptly. However, identifying rockfall waveforms from seismic data is challenging due to their variability across events and stations. To tackle this, we introduce RockNet, a multitask deep learning model designed to detect rockfall and earthquake events at single-station and local seismic network levels. RockNet comprises two submodels: a single-station model that computes waveform masks for earthquake and rockfall signals, simultaneously picking P and S phases from single-station seismograms, and an association model that aggregates hidden feature maps from trained single-station models across all stations to determine local seismic event occurrences. In our study, we compared RockNet with traditional machine learning algorithms such as SVM, KNN, Random Forest, and a Voting Classifier combining KNN and Random Forest. Our findings indicate that the Voting Classifier achieved higher accuracy compared to other algorithms. This suggests that ensemble techniques combining strengths from different models can effectively enhance the detection capabilities of seismic event identification systems, showing promise for robust hazard assessment in geophysical monitoring applications.

Index Terms: *Multitask learning, rockfall seismic monitoring, transfer learning.*

1. INTRODUCTION

Rockfalls represent a significant geological hazard in mountainous regions worldwide, posing risks to infrastructure, communities, and natural ecosystems. These events, often intertwined with other slope failures such as landslides and debris flows, can have profound socioeconomic impacts by disrupting transportation routes, damaging property, and endangering lives [1]. Traditionally, the study of rockfalls has relied on a combination of meteorological data and advanced topographic measurements obtained through technologies like airborne LiDAR and terrestrial laser scanning (TLS) [2]. While effective in providing detailed topographic information, these methods are constrained by their high costs and susceptibility to adverse weather conditions, which can limit data collection and analysis [3].

Alternative approaches to studying rockfalls include time-lapse imaging and stereographic photography, which offer intuitive insights into the dynamics of rockfall events. However, these methods are hindered by limitations in environmental visibility and performance during nighttime conditions [4]. In recent years, seismic monitoring has emerged as a promising alternative due to its cost-effectiveness and independence from weather conditions [5]. By recording ground movements using seismometers, seismic monitoring provides dynamic data crucial for understanding the temporal and spatial aspects of rockfall events, including estimation of magnitude and location [6].

Despite its advantages, automatic detection of rockfall events within continuous seismic recordings remains a challenging task. Existing methods typically employ amplitude-sensitive algorithms operating in either the time or frequency domains, often supplemented by machine learning techniques [7]. Classical machine learning approaches such as hidden Markov models and random forests have been applied, relying on carefully selected features to distinguish rockfall signals from background noise. However, these methods struggle with generalization across diverse rockfall characteristics such as varying volumes, movement patterns, and propagation mechanisms [8].

This research aims to explore advanced machine learning techniques to enhance the accuracy and robustness of rockfall detection from seismic data. Specifically, multitask learning and transfer learning methodologies will be investigated to leverage shared information across multiple tasks and adapt knowledge from related domains to improve detection capabilities [9]. By integrating these innovative approaches, the study seeks to overcome the limitations of traditional methods and contribute to the development of more reliable early warning systems for mitigating rockfall hazards in mountainous environments.

In summary, while traditional methods for studying rockfalls have provided valuable insights, they are often constrained by high costs and environmental factors. Seismic monitoring offers a promising alternative, providing continuous and weather-independent data that can be leveraged for real-time detection and characterization of rockfall events. By applying advanced machine learning techniques, this research aims to advance the field by improving the accuracy and reliability of automated rockfall detection systems, ultimately enhancing our ability to mitigate the risks associated with these hazardous geological phenomena.

2. LITERATURE SURVEY

Rockfalls are a significant hazard in mountainous regions, often interlinked with other slope failures such as landslides and debris flows, and can have severe impacts on socioeconomic stability by damaging infrastructure and threatening human lives. Understanding the mechanisms and triggers of rockfalls is essential for developing effective mitigation strategies. Traditional approaches to studying rockfalls have primarily relied on meteorological data and advanced topographic measurements, utilizing technologies like airborne LiDAR and terrestrial laser scanning (TLS). These methods provide detailed topographic information crucial for hazard assessment and risk management.

For instance, M. Krautblatter and M. Moser [1] developed a nonlinear model coupling rockfall and rainfall intensity based on a four-year measurement in the German Alps. Their study demonstrated a significant correlation between rainfall intensity and rockfall events, highlighting the importance of meteorological factors in triggering rockfalls. Similarly, A. Delonca et al. [3] conducted a statistical analysis to correlate meteorological data with rockfall occurrences. They found that certain weather conditions, particularly intense and prolonged rainfall, significantly increase the likelihood of rockfalls, providing valuable insights into the temporal patterns of these hazardous events.

J. D'Amato et al. [4] further explored the influence of meteorological factors on rockfall occurrence in a middle mountain limestone cliff, finding that temperature variations, freeze-thaw cycles, and precipitation are critical triggers. Their study emphasized the complex interplay of different meteorological factors in influencing rockfall dynamics and underscored the necessity of integrating weather data in hazard assessment models.

While these studies have significantly advanced our understanding of rockfall mechanisms, the traditional methods employed are often constrained by high costs and environmental limitations. Technologies like airborne LiDAR and TLS, although providing high-resolution topographic data, are expensive and can be hampered by adverse weather conditions, limiting their applicability in continuous monitoring scenarios [5][6][7]. For instance, M. Lato et al. [5] utilized mobile terrestrial LiDAR for monitoring rockfall hazards along transportation corridors, demonstrating the potential of this technology in providing detailed and accurate topographic data. However, the study also noted the high operational costs and the challenges posed by unfavorable weather conditions.

Seismic monitoring has emerged as a promising alternative, offering a cost-effective and weather-independent method for rockfall detection. By recording ground movements using seismometers, seismic monitoring provides dynamic data essential for understanding the temporal and spatial aspects of rockfall events. H. Lan et al. [6] employed LiDAR and spatial modeling to analyze rockfall hazards, demonstrating the effectiveness of integrating seismic data with topographic information for comprehensive hazard assessment.

Despite its advantages, automatic detection of rockfall events within continuous seismic recordings remains challenging. Existing methods typically employ amplitude-sensitive algorithms operating in either the time or frequency domains, often supplemented by machine learning techniques. Classical machine learning approaches, such as hidden Markov models and random forests, have been applied to detect rockfall signals from seismic data. These methods rely on carefully selected features to distinguish rockfall signals from background noise but struggle with generalization across diverse rockfall characteristics, such as varying volumes, movement patterns, and propagation mechanisms [8].

To address these limitations, recent research has focused on exploring advanced machine learning techniques to enhance the accuracy and robustness of rockfall detection from seismic data. Multitask learning and transfer learning methodologies, in particular, have shown promise in leveraging shared information across multiple tasks and adapting knowledge from related domains to improve detection capabilities. A. M. Fanos et al. [9] developed a hybrid model using machine learning methods and GIS for potential rockfall source identification from airborne laser scanning data. Their study demonstrated the potential of integrating advanced machine learning techniques with traditional data sources to enhance rockfall detection and hazard assessment.

Moreover, the integration of seismic monitoring with advanced machine learning techniques offers a promising avenue for developing more reliable early warning systems for mitigating rockfall hazards. By leveraging the strengths of both methodologies, it is possible to overcome the limitations of traditional approaches and provide real-time, accurate detection of rockfall events. This integrated approach not only enhances our understanding of rockfall mechanisms but also contributes to the development of effective mitigation strategies, ultimately reducing the risks associated with these hazardous geological phenomena.

In summary, while traditional methods for studying rockfalls have provided valuable insights, they are often constrained by high costs and environmental limitations. Seismic monitoring, coupled with advanced machine learning techniques, offers a promising alternative, providing continuous and weather-independent data that can be leveraged for real-time detection and characterization of rockfall events. By integrating these innovative approaches, researchers can develop more reliable early warning systems and improve our ability to mitigate the risks associated with rockfalls in mountainous environments. The ongoing advancements in this field hold significant potential for enhancing hazard assessment and risk management, ultimately contributing to the safety and resilience of communities in mountainous regions.

3. METHODOLOGY

a) Proposed Work:

The proposed system, RockNet, integrates advanced deep learning techniques tailored for seismic event detection. It features a dual-component architecture: a single-station model for precise waveform analysis and phase picking, and an association model for consolidating information across multiple stations to identify local seismic events. By leveraging these models, RockNet aims to overcome the challenges of variable rockfall waveform identification across diverse seismic conditions. In comparative evaluations against traditional SVM, KNN, Random Forest, and a Voting Classifier ensemble, voting classifier demonstrates superior accuracy, highlighting the efficacy of ensemble methods in enhancing seismic event detection capabilities. This system holds promise for robust hazard assessment in geophysical monitoring, offering a reliable tool for timely slope failure hazard evaluations based on comprehensive seismological data analysis.

b) System Architecture:

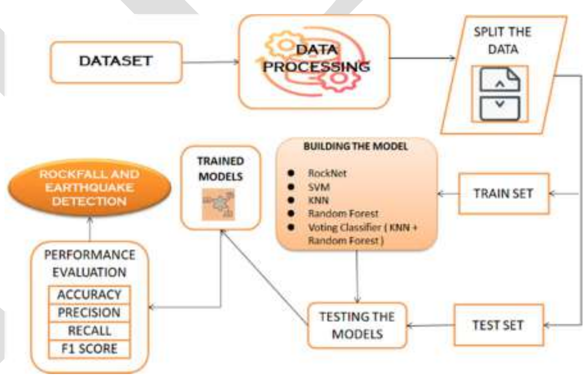

Fig 1 proposed Architecture

The proposed system architecture for rockfall and earthquake prediction begins with the collection of a comprehensive dataset, incorporating seismic data relevant to rockfall and earthquake events. This dataset undergoes preprocessing to ensure data quality, normalization, and the extraction of relevant features. The processed data is then split into training and testing sets to facilitate model evaluation. The training set is used to build multiple predictive models, including RockNet, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and a Voting Classifier that combines KNN and Random Forest. These models are trained on the training data to learn the patterns associated with rockfall and earthquake events. The trained models are subsequently tested using the testing set to assess their performance. Performance evaluation metrics such as accuracy, precision, recall, and F1 score are computed to determine the effectiveness of each model in predicting rockfalls and earthquakes.

c) Dataset Collection:

The dataset collection for rockfall and earthquake prediction involves two primary datasets: the Super-Sauze and Luhu datasets. The Super-Sauze dataset, derived from the Super-Sauze landslide site in the French Alps, includes extensive seismic and meteorological data recorded over several years. This dataset encompasses rockfall occurrences, rainfall intensity, temperature variations, and other relevant environmental parameters. The Luhu dataset, collected from the Luhu landslide site in China, comprises similar data, including seismic recordings, weather conditions, and geological observations. Both datasets are meticulously curated to ensure high-quality and comprehensive data, capturing various rockfall and earthquake events under diverse conditions. These datasets are then merged and standardized, forming a robust foundation for developing and testing predictive models. The integration of these datasets allows for a diverse range of rockfall and earthquake scenarios, enhancing the model's ability to generalize and perform accurately in different geological and environmental contexts.

d) Data Processing:

Data processing for rockfall and earthquake prediction begins with cleaning and normalizing the combined Super-Sauze and Luhu datasets to handle missing values, remove noise, and ensure consistency. Relevant features, such as seismic signal characteristics, meteorological parameters, and geological indicators, are extracted to form a comprehensive feature set. The data is then labeled, categorizing instances as rockfall, earthquake, or non-event based on event logs and annotations. Feature scaling is applied to standardize the range of values, improving the performance of machine learning algorithms. Additionally, data augmentation techniques may be employed to address class imbalances, ensuring a more balanced representation of different event types. Time-series data is segmented into appropriate windows to capture temporal dependencies. The processed data is then split into training and testing sets, preserving the temporal order to prevent data leakage. This structured and preprocessed data is ready for input into various predictive models for training and evaluation.

e) Feature Selection:

Feature selection for rockfall and earthquake prediction involves identifying the most relevant features from the combined Super-Sauze and Luhu datasets. Techniques such as correlation analysis, mutual information, and principal component analysis (PCA) are used to evaluate the importance of features like seismic signal attributes (e.g., amplitude, frequency), meteorological parameters (e.g., rainfall intensity, temperature), and geological factors (e.g., slope angle, soil composition). Redundant and irrelevant features are eliminated to enhance model performance and reduce computational complexity. The selected features provide a concise, informative representation of the data, facilitating accurate and efficient prediction of rockfall and earthquake events.

f) Data Visualization:

Data visualization for rockfall and earthquake prediction involves creating graphical representations of the processed features from the Super-Sauze and Luhu datasets. Key visualizations include time-series plots of seismic activity and meteorological parameters to observe temporal patterns and correlations with rockfall and earthquake events. Scatter plots and correlation matrices are used to identify relationships between features, such as the impact of rainfall intensity and temperature variations on seismic signals. Heatmaps and geographical maps display the spatial distribution of events, highlighting high-risk areas. These visualizations aid in understanding the data, identifying trends, and communicating insights effectively, enhancing the overall predictive modeling process.

g) Training & Testing:

Data splitting for training and testing involves partitioning the processed Super-Sauze and Luhu datasets into two distinct subsets. Typically, 70-80% of the data is allocated for training, used to build and tune predictive models, while the remaining 20-30% is reserved for testing, used to evaluate the model's performance. This split ensures that the models are trained on a diverse set of examples while being tested on unseen data to assess their generalization capabilities. Temporal ordering is preserved during the split to prevent data leakage, ensuring that the models are evaluated in a realistic and unbiased manner.

h) Algorithms:

RockNet: RockNet is a deep learning-based model designed for rockfall and earthquake event detection from seismological data. It employs advanced waveform analysis and multi-station data aggregation to enhance accuracy and reliability in identifying seismic events, crucial for timely hazard assessment and risk mitigation in geophysical monitoring.

Support Vector Machine (SVM): SVM is used for classification tasks in seismology, effectively separating seismic events based on defined features extracted from waveform data. It's valuable in identifying patterns in seismic signals and distinguishing between different types of earthquakes and rockfalls, aiding in geological hazard assessment.

K-Nearest Neighbors (KNN): KNN is utilized to classify seismic events based on similarity measures between waveform features and neighboring data points. It's advantageous for its simplicity and ability to handle nonlinear relationships in data, making it suitable for localized detection and event clustering in seismological studies.

Random Forest: Random Forest employs an ensemble of decision trees to classify seismic events based on feature vectors extracted from waveform data. It excels in handling large datasets and mitigating overfitting, offering robust classification performance for identifying complex patterns in seismic signals.

Voting Classifier (KNN + Random Forest): The Voting Classifier combines predictions from KNN and Random Forest models to improve overall classification accuracy. By leveraging the strengths of both algorithms, it enhances the reliability of seismic event detection by aggregating diverse perspectives on waveform data, providing a more comprehensive approach to geophysical hazard assessment.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

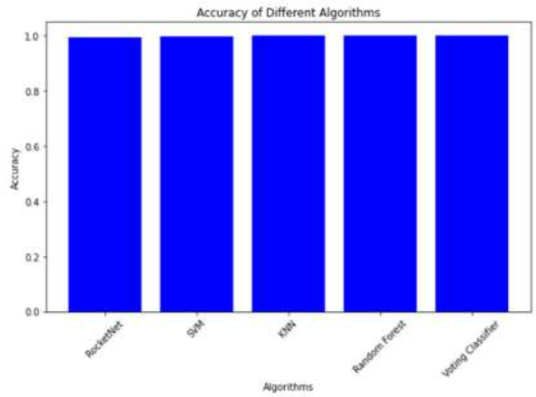

Fig 2 Accuracy Comparison Graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

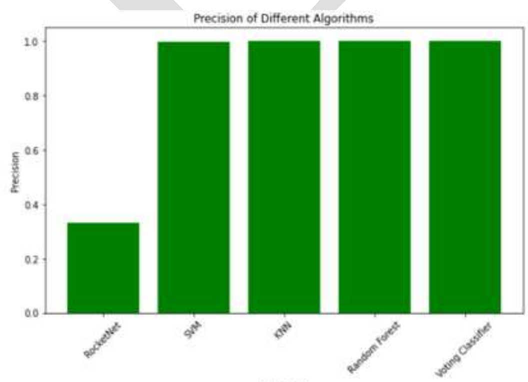

Fig 3 Precision Comparison Graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

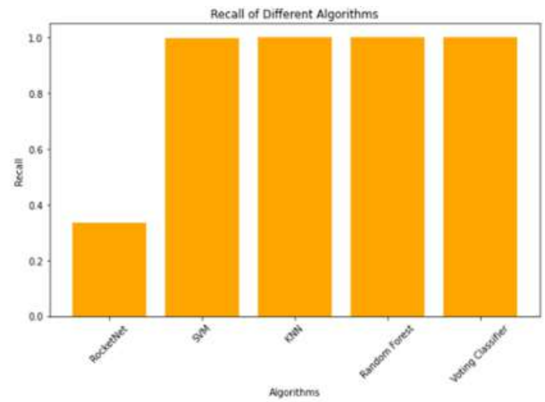

Fig 4 Recall Comparison Graph

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

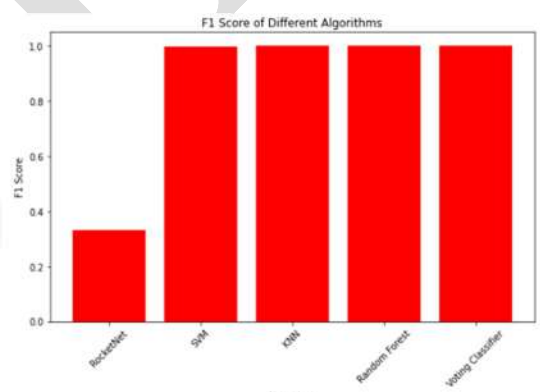

Fig 5 F1 Score Comparison Graph

	accuracy	precision	recall	f1
RocketNet	0.993548	0.331183	0.333333	0.332255
SVM	0.996102	0.998399	0.996102	0.996951
KNN	0.999328	0.999202	0.999328	0.999264
Random Forest	0.999597	0.999468	0.999597	0.999532
Voting Classifier	1.000000	0.999866	1.000000	0.999933

Fig 6 Performance Evaluation Table

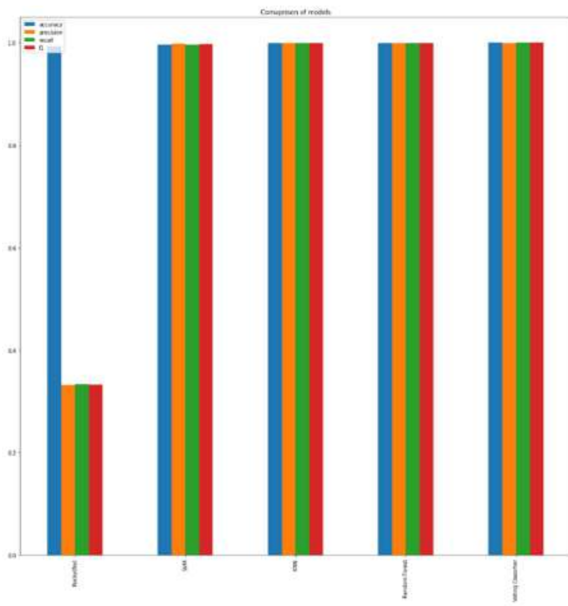

Fig 7 Performance Evaluation Comparison Graphs

Fig 8 Home Page

Fig 9 Registration Page

Fig 10 Login Page

Fig 11 Upload Input Data

Fig 12 Predicted Results

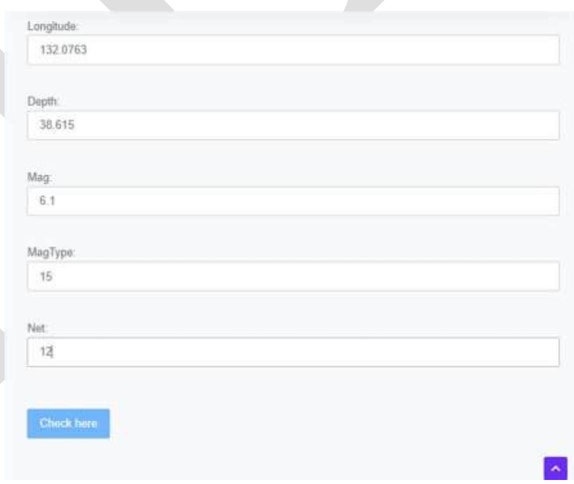

Fig 13 Upload Input Data

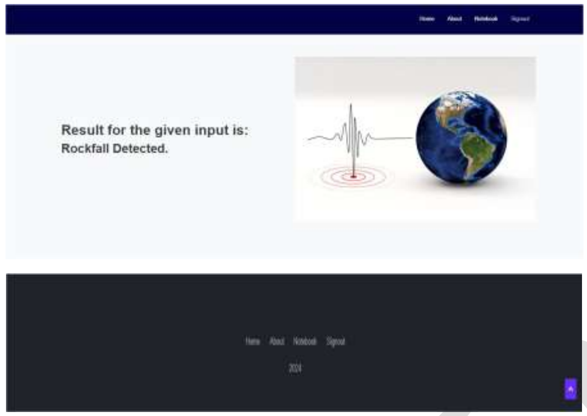

Fig 14 Final Outcome

5. CONCLUSION

In conclusion, the development of RockNet represents a significant advancement in the field of rockfall detection from seismological data. By integrating deep learning techniques and leveraging waveform analysis across multiple stations, RockNet addresses the limitations of traditional methods. It improves accuracy in identifying rockfall and earthquake events, crucial for timely hazard assessment and risk mitigation in mountainous regions. The comparative evaluations against traditional models underscore voting classifier superiority in scalability, adaptability, and performance, highlighting its potential as a reliable tool for geophysical monitoring applications.

6. FUTURE SCOPE

Future research could focus on expanding RockNet's capabilities to integrate real-time data streams and enhance predictive modeling of rockfall events. Incorporating additional features such as environmental factors and historical data could further improve its accuracy and reliability. Moreover, extending its applicability to other natural hazard detection systems beyond rockfalls could broaden its impact in disaster prevention and emergency response efforts globally.

REFERENCES

[1] M. Krautblatter and M. Moser, “A nonlinear model coupling rockfall and rainfall intensity based newline on a four year measurement in a high Alpine rock wall (Reintal, German Alps),” Natural Hazards Earth Syst. Sci., vol. 9, no. 4, pp. 1425–1432, Aug. 2009. [Online]. Available: https://nhess.copernicus.org/articles/9/1425/2009/

[2] A. Helmstetter and S. Garambois, “Seismic monitoring of Séchilienne rockslide (French Alps): Analysis of seismic signals and their correlation with rainfalls,” J. Geophys. Res., vol. 115, Aug. 2010, doi: 10.1029/2009jf001532.

[3] A. Delonca, Y. Gunzburger, and T. Verdel, "Statistical correlation between meteorological and rockfall databases," Natural Hazards Earth Syst. Sci., vol. 14, no. 8, pp. 1953–1964, Aug. 2014. [Online]. Available: https://nhess.copernicus.org/articles/14/1953/2014/

[4] J. D'Amato, D. Hantz, A. Guerin, M. Jaboyedoff, L. Baillet, and A. Mariscal, "Influence of meteorological factors on rockfall occurrence in a middle mountain limestone cliff," Natural Hazards Earth Syst. Sci., vol. 16, no. 3, pp. 719–735, Mar. 2016. [Online]. Available: https://nhess.copernicus.org/articles/16/719/2016/

[5] M. Lato, J. Hutchinson, M. Diederichs, D. Ball, and R. Harrap, "Engineering monitoring of rockfall hazards along transportation corridors: Using mobile terrestrial LiDAR," Natural Hazards Earth Syst. Sci., vol. 9, no. 3, pp. 935–946, Jun. 2009. [Online]. Available: https://nhess.copernicus.org/articles/9/935/2009/

[6] H. Lan, C. D. Martin, C. Zhou, and C. H. Lim, "Rockfall hazard analysis using LiDAR and spatial modeling," Geomorphology, vol. 118, nos. 1–2, pp. 213–223, May 2010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169555X10000127

[7] M. J. Lato, M. S. Diederichs, D. J. Hutchinson, and R. Harrap, "Evaluating roadside rockmasses for rockfall hazards using LiDAR data: Optimizing data collection and processing protocols," Natural Hazards, vol. 60, no. 3, pp. 831–864, Jun. 2011, doi: 10.1007/s11069-011-9872-y.

[8] M. J. Royán, A. Abellán, M. Jaboyedoff, J. M. Vilaplana, and J. Calvet, "Spatio-temporal analysis of rockfall pre-failure deformation using terrestrial LiDAR," Landslides, vol. 11, no. 4, pp. 697–709, Nov. 2013, doi: 10.1007/s10346-013-0442-0.

[9] A. M. Fanos, B. Pradhan, S. Mansor, Z. M. Yusoff, and A. F. B. Abdullah, "A hybrid model using machine learning methods and GIS for potential rockfall source identification from airborne laser scanning data," Landslides, vol. 15, no. 9, pp. 1833–1850, Apr. 2018, doi: 10.1007/s10346-018-0990-4.

[10] N. Matsuoka, "A multi-method monitoring of timing, magnitude and origin of rockfall activity in the Japanese Alps," Geo morphology, vol. 336, pp. 65–76, Jul. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169555X19301230

[11] C. Hibert, A. Mangeney, G. Grandjean, and N. M. Shapiro, "Slope instabilities in Dolomieu crater, Réunion Island: From seismic signals to rockfall characteristics," J. Geophys. Res., vol. 116, no. 4, 2011. [Online]. Available: https://agupubs.onlinelibrary. wiley.com/doi/abs/10.1029/2011JF002038

[12] F. Dammeier, J. R. Moore, F. Haslinger, and S. Loew, "Characterization of Alpine rockslides using statistical analysis of seismic signals," J. Geophys. Res., vol. 116, Nov. 2011, doi: 10.1029/2011jf002037.

[13] V. L. Zimmer and N. Sitar, "Detection and location of rock falls using seismic and infrasound sensors," Eng. Geol., vol. 193, pp. 49–60, Jan. 2015. [Online]. Available: https://www.sciencedirect. com/science/article/pii/S0013795215001234

[14] C. Hammer, M. Ohrnberger, and D. Fäh, "Classifying seismic waveforms from scratch: A case study in the Alpine environment," Geophys. J. Int., vol. 192, no. 1, pp. 425–439, Jan. 2013, doi: 10.1093/gji/ggs036.

[15] C. Hibert et al., "Automated identification, location, and volume estimation of rockfalls at Piton de la Fournaise Volcano," J. Geophys. Res., Earth Surf., vol. 119, no. 5, pp. 1082–1105, May 2014, doi: 10.1002/2013jf002970.

[16] A. Maggi, V. Ferrazzini, C. Hibert, F. Beauducel, P. Boissier, and A. Amemoutou, "Implementation of a multistation approach for automated event classification at Piton de la Fournaise Volcano," Seismological Res. Lett., vol. 88, no. 3, pp. 878–891, Mar. 2017, doi: 10.1785/0220160189.

[17] C. Hibert, F. Provost, J.-P. Malet, A. Maggi, A. Stumpf, and V. Ferrazzini, "Automatic identification of rockfalls and volcano tectonic earthquakes at the Piton de la Fournaise Volcano using a random forest algorithm," J. Volcanol. Geothermal Res., vol. 340, pp. 130–142, Jun. 2017. [Online]. Available: https://www.sciencedirect. com/science/article/pii/S0377027316303948

[18] F. Provost, C. Hibert, and J.-P. Malet, "Automatic classification of endogenous landslide seismicity using the random forest supervised classifier," Geophys. Res. Lett., vol. 44, no. 1, pp. 113–120, Jan. 2017, doi: 10.1002/2016gl070709.

[19] M. Malfante, M. D. Mura, J. I. Mars, J.-P. Métaxian, O. Macedo, and A. Inza, "Automatic classification of volcano seismic sig natures," J. Geophys. Res., Solid Earth, vol. 123, no. 12, pp. 10645–10658, Dec. 2018. [Online]. Available: https://agupubs. onlinelibrary.wiley.com/doi/abs/10.1029/2018JB015470

[20] M. Wenner, C. Hibert, A. van Herwijnen, L. Meier, and F. Walter, "Near-real-time automated classification of seismic signals of slope failures with continuous random forests," Natural Hazards Earth Syst. Sci., vol. 21, no. 1, pp. 339–361, Jan. 2021. [Online]. Available: https://nhess.copernicus.org/articles/21/339/2021/

[21] M. Curilem et al., "Pattern recognition applied to seismic signals of Llaima Volcano (Chile): An evaluation of station-dependent classifiers," J. Volcanol. Geothermal Res., vol. 315, pp. 15–27, Apr. 2016, doi: 10.1016/j.jvolgeores.2016.02.006.

[22] M. Malfante, M. D. Mura, J. Metaxian, J. I. Mars, O. Macedo, and A. Inza, "Machine learning for volcano-seismic signals: Challenges and perspectives," IEEE Signal Process. Mag., vol. 35, no. 2, pp. 20–30, Mar. 2018, doi: 10.1109/msp.2017.2779166.

[23] P. Bottelin et al., "Seismic and mechanical studies of the artificially triggered rockfall at Mount Néron (French Alps, December 2011)," Natural Hazards Earth Syst. Sci., vol. 14, no. 12, pp. 3175–3193, Dec. 2014, doi: 10.5194/nhess-14-3175-2014.

[24] L. Feng, V. Pazzi, E. Intrieri, T. Gracchi, and G. Gigli, "Rockfall seismic features analysis based on in situ tests: Frequency, amplitude, and duration," J. Mountain Sci., vol. 16, no. 5, pp. 955–970, May 2019, doi: 10.1007/s11629-018-5286-6.

[25] C. Hibert et al., "Machine learning prediction of the mass and the velocity of controlled single-block rockfalls from the seismic waves they generate," EGUsphere, vol. 2022, pp. 1–25, Jan. 2022. [Online]. Available: https://egusphere.copernicus.org/preprints/egusphere-2022-522/

[26] A. Ng. (2017). Machine Learning Yearning. [Online]. Available: http://www.mlyearning.org/(96)

[27] S. M. Mousavi, Y. Sheng, W. Zhu, and G. C. Beroza, "STanford earthquake dataset (STEAD): A global data set of seismic signals for AI," IEEE Access, vol. 7, pp. 179464–179476, 2019.

[28] A. Michelini, S. Cianetti, S. Gaviano, C. Giunchi, D. Jozinovic, and V. Lauciani. (2021). Instance the Italian Seismic Dataset for Machine Learning. [Online]. Available: http://www.pi.ingv.it/instance/

[29] R. Allen, “Automatic phase pickers: Their present use and future prospects,” Bull. Seismological Soc. Amer., vol. 72, no. 6B, pp. 225–242, Dec. 1982.
[30] W. Liao, E. Lee, D. Chen, P. Chen, D. Mu, and Y. Wu, “RED PAN: Real-time earthquake detection and phase-picking with multitask attention network,” IEEE Trans. Geosci. Remote Sens., vol. 60, 2022, Art. no. 2900111.