Proceedings of the 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC-2024)
IEEE Xplore Part Number: CFP24BC3-ART; ISBN: 979-8-3503-7519-0

2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC) | 979-8-3503-7519-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICAAIC60222.2024.10575330

Dynamic Landslide Prediction, Monitoring, and Early Warning with Explainable AI: A Comprehensive Approach

Kristin Elizabeth Binu
Dept. of Computer Science and Engineering
Rajagiri School of Engineering & Technology
Rajagiri Valley P O, Kochi, India
kristinelizabethbinu@gmail.com

Merin Jose
Dept. of Computer Science and Engineering
Rajagiri School of Engineering & Technology
Rajagiri Valley P O, Kochi,India
merinjose2810@gmail.com

Lakshmi Thampi Anoopkumar
Dept. of Computer Science and Engineering
Rajagiri School of Engineering & Technology
Rajagiri Valley P O, Kochi, India
lakshmitanoop25@gmail.com

Preetha K. G.
Dept. of Computer Science and Engineering
Rajagiri School of Engineering & Technology
Rajagiri Valley P O, Kochi, India
preetha_kg@rajagiritech.edu.in

Maria Sunil
Dept. of Computer Science and Engineering
Rajagiri School of Engineering & Technology
Rajagiri Valley P O, Kochi, India
mariasunil1733@gmail.com

***Abstract*—Landslides are a major threat to infrastructure, human lives, and the environment. Therefore, early warning systems and precise forecasting are essential for reducing their effects. This study investigates how to enhance landslide prediction models using Explainable Artificial Intelligence (XAI) methodologies. Intending to improve complex machine learning models' interpretability and transparency, XAI seeks to improve comprehension and confidence in the model's predictions. XAI methodologies used are SHapley Additive exPlanations (SHAP), LIME (Local Interpretable Model-agnostic Explanations), and feature importance analysis. These techniques produce comprehensible explanations for each forecast and assist in determining the most significant variables in landslide prediction. The proposed XAI-enhanced landslide prediction model demonstrates promising results in terms of accuracy and interpretability. The research reported here helps to design more potent early warning systems for landslides by advancing explainable AI applications in geoscience and disaster risk reduction.**

Keywords*—Landslide, Explainable Artificial Intelligence (XAI), Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), Early Warning

I. Introduction

Geologically, landslides are becoming more frequent and dangerous for both urban and rural areas [1]. They cause massive damage, human casualties, and loss of property all over the world. Several variables cause landslides to occur. Slope stability is a major factor in the occurrence of a landslide. Topographical factors, including the composition of the rock and soil, the steepness of the slope, and the existence of faults or fractures have a significant effect on slope stability. The weather and climate conditions, especially prolonged periods of rainfall and ice melting, are frequently responsible for landslides[2]. Rainfall that is heavy or persistent can saturate the soil, decreasing its cohesiveness and adding to its weight, lowering the stability of the slope. Slope stability may be further weakened by increased water infiltration into the ground as a result of rapid snowmelt. Additionally, minimizing water flow and limiting soil erosion, and plant cover is essential for stabilizing slopes[3]. This natural stabilization can be disturbed by deforestation, urbanization, and changes in land use, which makes slopes more vulnerable to landslides. Comprehending these variables is imperative to alleviate the hazards linked to landslides and execute efficacious hazard mitigation tactics [4].

Landslide susceptibility is influenced by many factors, including geological, meteorological, and topographical variables [5,6]. Traditional landslide prediction models often rely on complex algorithms that, while capable of high accuracy, lack transparency and interpretability. The emerging field of Explainable Artificial Intelligence (XAI)[7,8] caters to this concern by providing comprehensive explanations for the results given by the complex models, fostering trust, and enabling more informed decision-making.

In this work, XAI techniques are utilized to create a landslide prediction model that is very accurate and offers insights into the factors affecting its forecasts. By utilizing XAI, it is easy to decipher the complex interrelationships among these variables and offer a more profound comprehension of the motivations underlying landslip incidents. To provide a thorough understanding of landslide susceptibility, the model is trained on a large dataset that incorporates geological, meteorological, and topographical characteristics. The sole aim of the study is to give actionable insights to government officials and geologists derived from the model's prediction.

By validating model predictions against ground-truth data from various temporal and geographical contexts, you can increase the reliability of landslip prediction using SHAP and LIME models. This ensures that the model remains robust even in the face of changing environmental conditions. It also incorporates feedback mechanisms as well as continuously improving the model based on expert insights and real-world observations. Thereby, dependability in real-world applications is strengthened.

For ease of understanding, the paper is organized in the following manner. The relevant literature in the fields of Explainable AI and landslide prediction is described in Section 2. The design and execution processes involved in creating the suggested model are thoroughly explained in Section 3. Section 4 comprises illustrations of the results along with their explanations. In Section 5, the conclusion to the work is discussed.

II. RELATED RESEARCH

The literature has put out a wide range of techniques for identifying landslides which includes traditional methods and AI-based methods. An XGBoost machine learning technique proposed in [9] is used to create a short-term landslide prediction model. XGBoost produced the greatest outcomes once the models were put into practice and evaluated to see which prediction model was best. The outcomes were contrasted with the most recent landslide analysis efforts, which mostly concentrated on estimating susceptibility maps.

To find a more accurate prediction model, many machine learning techniques and SIGMA were applied to the same region and data [10]. To comprehend the significance of features in the relationships and outputs of the predictive model, explainable artificial intelligence approaches are applied. The best attributes for short-term forecasts were determined with the use of this investigation. Landslides are categorized using an Autoencoder reconstruction error with a threshold. A reconstruction error was categorized as a landslip if it exceeded the selected threshold.

To assess the risk of landslides, classifiers from machine learning and deep learning are combined. Six models use the fourteen landslide-impacting elements that are obtained from remote sensing, geological data, and DEM as input variables. The findings show that when it comes to forecasting landslides caused by intense rainfall, the combined classifiers of Sparse Autoencoder (SpAE) with RF and Stacked Autoencoder (StAE) with Random Forest (RF) perform better than the individual classifiers of Support Vector Machine (SVM), RF, StAE, and SpAE[11].

Explainable AI [12] uses a simple deep learning model that is meant to make diagnosis easier and avoid overfitting. The model structure consists of an ANN, or fully connected network, plus extra parts for stability and generalization. The model's input consists of thirteen features: one geological feature that has been processed through an embedding layer and twelve numerical features that have been normalized before input. For practical reasons, the model treats categorical data as numeric.

III. PROPOSED METHOD

A multi-step procedure is designed to use machine learning techniques to predict landslides in a given area [16]. The architecture diagram of the proposed model is given in Figure 1.

The early phases of the architecture are devoted to preprocessing and data collection. Data on landslides is gathered from the available sources and pre-processed. It consists of several determining factors like the amount of precipitation and rainfall patterns, and properties of land like aspect, curvature, elevation, slope, etc. The flow and vegetation index are also considered. The study makes use of the normalized version of the Muzaffarabad-Pakistan Landslide Prediction dataset [13]. Other datasets are available in [14,15].

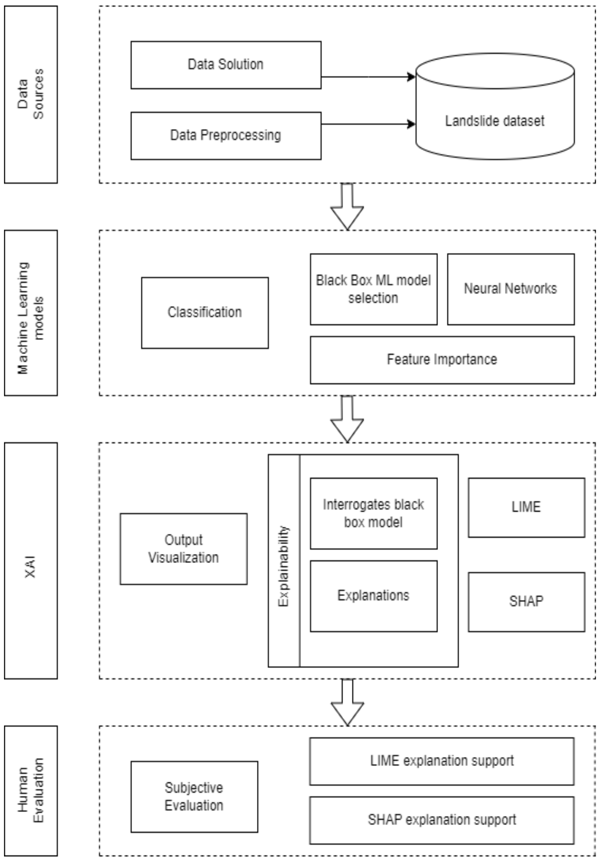

Fig. 1. Proposed Model

In the second phase, black box models are selected and machine learning models are used for categorization. These models identify the important factors impacting the predictions by using feature-importance data. Neural networks added to the processing step improve the model's ability to identify complex patterns in the input. A machine learning approach called Random Forest is selected. Random Forests can identify the most important features or variables contributing to landslide occurrence.

These features can include factors such as rainfall intensity, earthquakes, lithology, soil type, soil profile, soil flow, land cover, elevation, slope angle, slope aspect, vegetation cover, seismic activity, and human activities. Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI) are also taken into consideration. This is because the density and health of vegetation also greatly influence the soil profile. By analyzing feature importance, interventions or mitigation strategies can be prioritized to target the most influential factors.

In the third phase, explainability is considered as a crucial element. An explainable AI model is used to interpret the random forest model's predictions. For this, the algorithms SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are used. These algorithms offer transparency and facilitate an understanding of the decision-making process by elucidating the rationale behind particular model results.

The Shapley value, rooted in cooperative game theory, measures the individual contribution of each feature in a model's prediction. It's calculated as the weighted average of how adding a feature influences predictions across all possible combinations of features. This method accounts for the varying impact of features depending on their interaction with others in the model. The algorithm for the SHAP model is described in Table 1.

Table 1: Algorithm for SHAP

1. Start 2. Input Dataset 3. Use a Trained machine learning model (The proposed method uses random forests). 4. Initialize the SHAP explainer object with the trained machine learning model and dataset. 5. Compute SHAP values for all instances in the dataset. 6. Generate summary plots or statistics to visualize the overall impact of features on model predictions. 7. Interpret individual predictions //For specific instances of interest, analyze individual SHAP values to understand why the model made a particular prediction. 8. Use force plots or other visualization techniques to illustrate each feature's influence on the model's prediction for that instance. 9. Feature importance ranking-Rank features based on their average absolute SHAP values across all instances. 10. Model validation and refinement-Validate the SHAP-explained model's performance using appropriate evaluation metrics and techniques. 11. Refine the model based on insights gained from interpreting SHAP values, such as feature selection, hyperparameter tuning, or data preprocessing. 12. Stop.

The SHAP values are computed using Equation 1. Shapley value (ϕ_i) signifies the impact of feature i on the overall prediction. N represents the collection of all features, v(N) denotes the outcome when no features are taken into account and n represents the number of features in N. The feature i is contained in the subset S.

$$\emptyset_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!} \left[v(S \cup \{i\}) - v(S) \right] \quad (1)$$

Equation 2 consists of $g(z')$ which represents the model's output for a given feature vector x. g is the explanation model, and ∅i is the Shapley value for feature i.z'_i is the simplified feature vector without feature i. M is the number of features and v(∅) is the model output when all features are absent. The summation of Shapley values of each feature is taken to estimate the model outcome.

$$g(z') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i z'_i \quad (2)$$

LIME is independent of the random forest model. It works locally to provide reasoning for the prediction. The reasonings provided by LIME for each result x are obtained using Equation 3.

$$\emptyset(x) = argmin_{g \in G}\, L(f, g, \pi_x) + \Omega(g) \quad (3)$$

The algorithm for the LIME model is described in Table 2.

Table 2: Algorithm for LIME

1. Start 2. Input Dataset 3. Choose a specific instance from the dataset for which you want to generate an explanation 4. Fit a local interpretable model to the samples and their corresponding predictions. 5. Calculate feature importance// Extract feature weights or coefficients from the fitted interpretable model to determine the importance of each feature for the prediction of the selected instance. Positive coefficients indicate features that positively contribute to the prediction, while negative coefficients indicate features that negatively contribute. 6. Visualize the feature importance scores or coefficients to understand which features are most influential for the prediction of the selected instance 7. Identify which features played a significant role in the prediction and how their values influenced the outcome. 8. Stop

This study makes use of random forests for G. G is conventionally taken to be the set of interpretable models in this mathematical equation.

g ∈ G, is the measure of closeness between an instance z and x. Ω(g) is the measure of complexity of the explanation given by g ∈ G. L measures the inconsistency degree between the approximation provided by g and the actual function f within the scope defined by π(x). Since LIME is model agnostic, it is important to minimize loss L.

Using the explainable AI model, the model outputs are visualized in the last phases. The questioning of the random forest model is made easier by this visualization, which permits a thorough analysis of the findings. Subjective assessment is also carried out to make sure the results meet human norms and expectations. This is done using real-time data. A human-centric viewpoint tests the model's predictions against domain expertise and common sense, improving the system's overall reliability. To provide a comprehensive system for landslide prediction or analysis, the suggested architecture includes explainability, machine learning models, knowledge graph construction, data preparation, and subjective evaluation.

IV. Results and Discussions

The results of the proposed model and how well the Random Forest model may be interpreted to produce accurate landslide forecasts are examined. Both the SHAP and LIME models use the full training dataset to offer both global and local explanations.

Figures 2 & 3 illustrate the interpretation of the positive and negative cases of a landslide event using the LIME model. The rightmost value denotes the prediction given by the LIME prediction model for the given test vector.

In Figure 2, the landslide is predicted with 94% confidence. Because the elevation is equal to 1, profile is greater than 4, precipitation is greater than 4, aspect ratio is greater than 2, curvature is less than 2, NDWI is greater than

2, earthquake is greater than 2 and NDVI is greater than 2, the model predicted this event to be a landslide event.

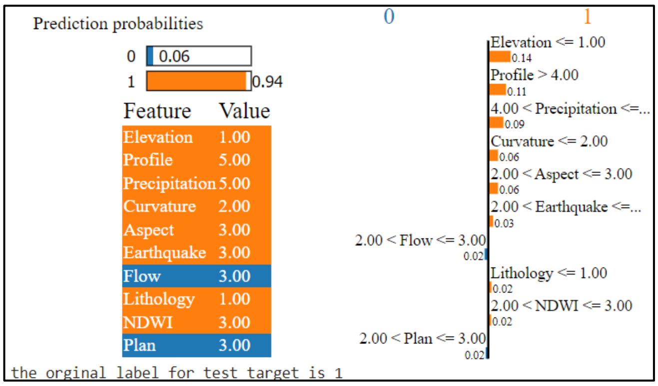

Fig. 2. Prediction of Landslide Event using LIME Model

Figure 3 gives the interpretation of a non-landslide event with 83% confidence. Since the precipitation is less than 3, NDVI is greater than 4, elevation is greater than 2, profile is less than 2, earthquake is less than 2, aspect and curvature.

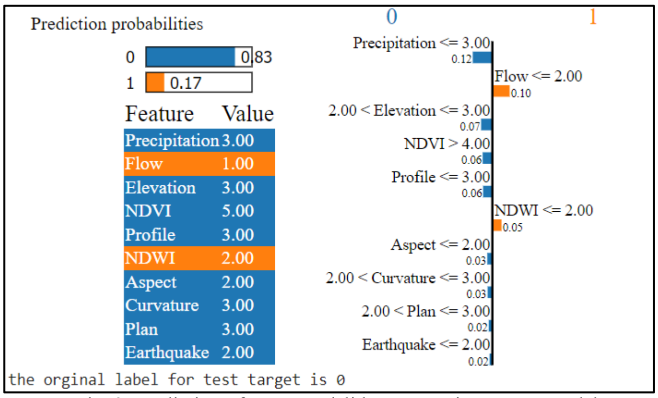

Fig. 3. Prediction of Non-Landslide Event using LIME Model

Figure 4 represents a bar graph showing the relative importance of features in the landslide prediction model using SHAP. The features are marked on the Y-axis, and their relative importance is marked on the X-axis. The longer the bar, the greater will be the precedence of the corresponding feature for predicting landslides.

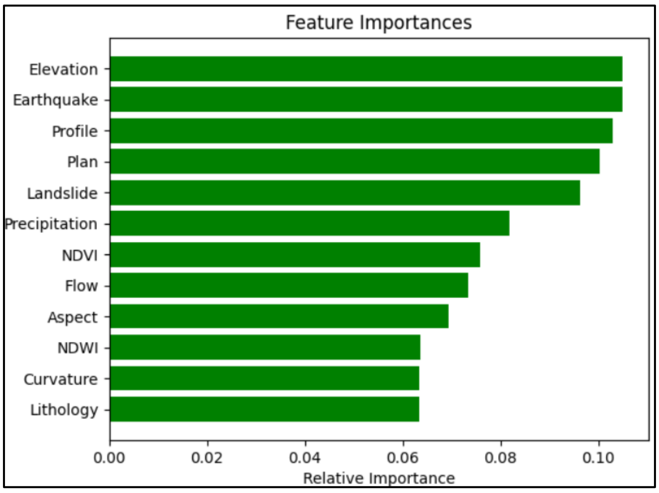

Fig. 4. Landslide Event Prediction using SHAP model

Figure 5 shows the summary plot of SHAP analysis for a non-landslide event. The average influence on the model's output magnitude of each feature is shown in the plot. The features are listed on the Y-axis, and their corresponding magnitude of impact is shown on the X-axis. The red bar indicates a positive influence on the result, and a negative influence is indicated by the blue bar. The longer the red part of the bar (and the shorter the blue part of the bar), the greater the influence of the feature on the model's output and vice versa. The plot shows that the "Flow" feature has the largest positive influence on the model's output. In contrast, the "Lithology" feature has the largest negative impact, i.e., on average, higher flow values tend to increase the model's prediction of a landslide. In comparison, higher lithology values tend to decrease the odds of a positive landslide event.

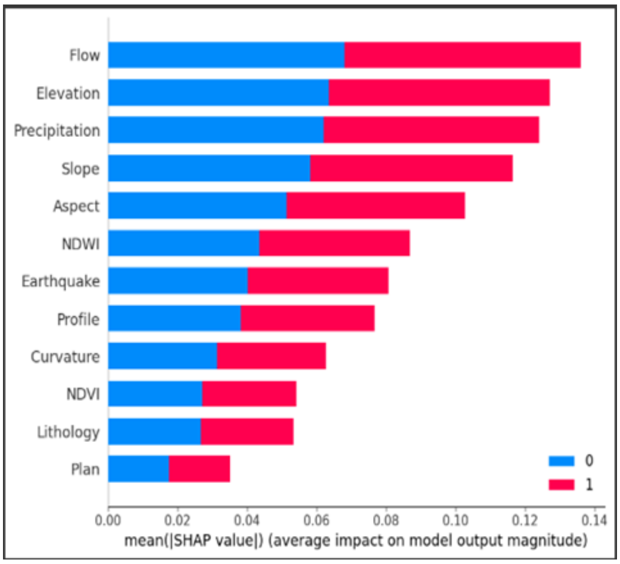

Fig. 5. Non-Landslide Event Prediction using the SHAP model

Sorted by relevance, Figure 6 displays the dispersal of SHAP values for every feature. The SHAP values are plotted on the X-axis against the features on the Y-axis. Each point corresponds to an instance from the dataset. The color of the point indicates the magnitude of the influence of a certain attribute. Red indicates the attribute to be associated with a large value while blue indicates association with a small value.

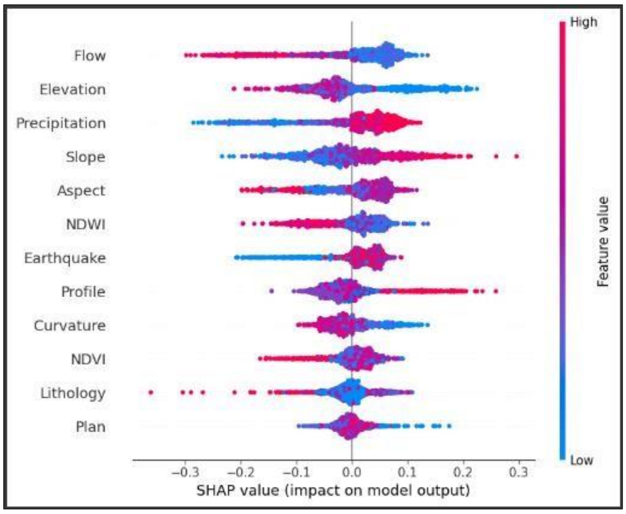

Fig. 6. Dispersal of SHAP values for each feature

Whether a feature value results in a positive or negative forecast is indicated by the point's horizontal location.

Higher values (red dots) in the positive direction indicate a larger contribution as is the case for the feature precipitation, slope, and profile. They strongly influence the likelihood of a landslide.

SHAP dependence plots in Figure 7 illustrate how a given feature affects the entire dataset. The aspect values are plotted on the X-axis against the aspect's SHAP value on the Y-axis for several samples are shown in the figure. Interaction effects drive the vertical dispersion of SHAP values at a single feature value, and a different feature is selected for coloring to emphasize potential interactions. The variance is also displayed on the Y-axis in SHAP dependency.

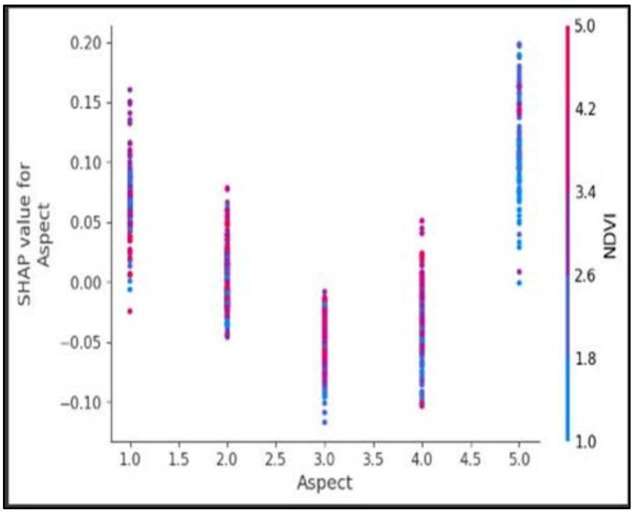

Fig. 7. Dependence plot for the entire dataset

The local interpretation of a landslide incident is depicted in Figure 8. A positive influence on the result is indicated by the red bar, and a negative influence is indicated by the blue bar. The lithology feature has a 0.36 influence on how a landslide turns out.

In the upper-right corner, the likelihood value of a landslide occurring, or the positive case, is represented by f(x)=0.91 in the machine learning model. The expected value (EV) is shown at the bottom of the figure, E[f(x)]=0.484. The actual percentage of positive cases from the training dataset that was used to develop the ML model is called the EV, which is also referred to as the background data in the SHAP technique. The EV can be viewed as a beginning point because it represents a crudely expected outcome.

The result can be obtained by summing the SHAP values of each feature and EV. Stated differently, the SHAP values can show the relative contributions of each feature to the result when EV is used as the beginning point and Z(x) is used as the terminus. The SHAP model allows for both global and local interpretations, whereas the LIME model only allows for local interpretation for each instance. With its graphical displays, SHAP produces results that are easier to interpret and yield more accuracy. In comparison to LIME, SHAP has increased computational complexity.

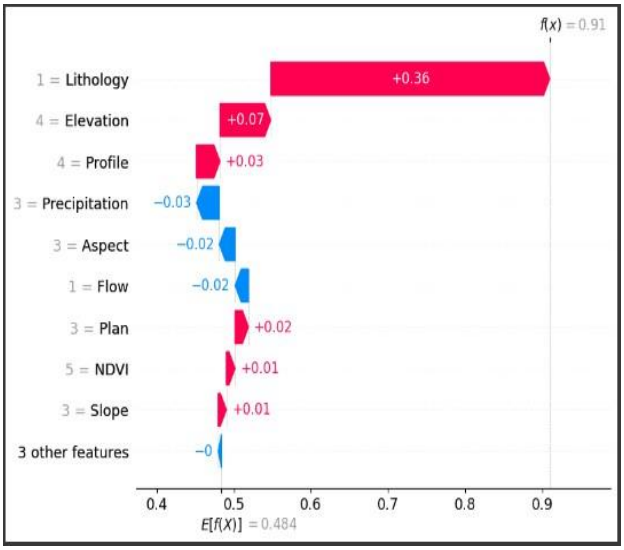

Fig. 8. Local Interpretation of Landslide Incident

V. CONCLUSIONS

Using Explainable Artificial Intelligence (AI) tools, given a comprehensive methodology for dynamic landslip prediction, monitoring, and early warning in this research study. The work integrated AI capabilities with explainability and interpretability principles to answer the pressing demand for better methodologies in landslip prediction. The predictability of the decision-making process is improved by the proposed method, which makes it clear and transparent to stakeholders. Furthermore, the significance of real-time monitoring systems in recording dynamic changes in terrain stability and climatic conditions has been emphasized by the research.

In the paper, performance was enhanced by the use of explainable AI approaches. The suggested model provides a clear explanation of the parameters that contribute more to the likelihood of landslides.

The proposed system allows for continuous surveillance of areas susceptible to landslides, so aiding rapid identification and reaction. Data from many sources, including weather sensors, satellite imaging, and ground-based monitoring stations, are integrated. By using Explainable AI models such as LIME and SHAP to produce risk assessments and actionable insights, allowing for preventive steps to be taken to lessen the impact of possible landslide incidents and ultimately save lives and property damage. The increased infrastructure and community resilience to landslide hazards will ultimately help achieve the more general objective of sustainable disaster risk management by using explainable AI.

The complexity and variability of environmental factors that contribute to landslip occurrence is a practical limitation of utilizing explainable AI for landslide prediction. It involves enormous volumes of data, requires a GPU for processing, and has higher computational complexity.

Stakeholders, including geologists, civil engineers, and local authorities, can obtain practical insights for more informed decision-making in landslide risk management through thorough analysis and visualization of the model outputs. In addition to improving confidence in the forecasts, the XAI-enhanced model's openness and interpretability expand the field of XAI applications in geoscience and catastrophe risk reduction.

Future Research may concentrate on creating more complex explainable artificial intelligence models that are better equipped to manage nonlinear relationships and interactions between predictors. Using integrated models could lead to more precise outcomes. Furthermore, investigating cutting-edge data fusion methods to combine various data sources, like historical records and data from remote sensing, may enhance the precision and dependability of landslide forecasts.

REFERENCES

[1] Jindal, Harsh, Ayush Yadav, Abhinav Sehgal, Sugandha Sharma, Ankit Panigrahi, Dipesh Ranjan, Abhoy Gorai, and Manas Tiwari. "Geospatial Landslide Prediction–Analysis & Prediction From 2018-2022." Journal of Pharmaceutical Negative Results (2023): 2589-2599.

[2] Sheng, Yifan, Guangli Xu, Bijing Jin, Chao Zhou, Yuanyao Li, and Weitao Chen. "Data-driven landslide spatial prediction and deformation monitoring: a case study of Shiyan City, China." Remote Sensing 15, no. 21 (2023): 5256.

[3] Chang, Zhilu, Faming Huang, Jinsong Huang, Shui-Hua Jiang, Yuting Liu, Sansar Raj Meena, and Filippo Catani. "An updating of landslide susceptibility prediction from the perspective of space and time." Geoscience Frontiers 14, no. 5 (2023): 101619.

[4] Nava, Lorenzo, Edoardo Carraro, Cristina Reyes-Carmona, Silvia Puliero, Kushanav Bhuyan, Ascanio Rosi, Oriol Monserrat et al. "Landslide displacement forecasting using deep learning and monitoring data across selected sites." Landslides 20, no. 10 (2023): 2111-2129.

[5] Steger, Stefan, and Christian Kofler. "Statistical modeling of landslides: landslide susceptibility and beyond." In Spatial Modeling in GIS and R for Earth and Environmental Sciences, pp. 519-546. Elsevier, 2019.

[6] Meena, Sansar Raj, Silvia Puliero, Kushanav Bhuyan, Mario Floris, and Filippo Catani. "Assessing the importance of conditioning factor selection in landslide susceptibility for the province of Belluno (region of Veneto, northeastern Italy)." Natural Hazards and Earth System Sciences 22, no. 4 (2022): 1395-1417.

[7] Pradhan, Biswajeet, Abhirup Dikshit, Saro Lee, and Hyesu Kim. "An explainable AI (XAI) model for landslide susceptibility modeling." Applied Soft Computing 142 (2023): 110324.

[8] Dahal, Ashok, and Luigi Lombardo. "Explainable artificial intelligence in geoscience: A glimpse into the future of landslide susceptibility modeling." Computers & Geosciences 176 (2023): 105364.

[9] Xu, Jiancong, Yu Jiang, and Chengbin Yang. "Landslide Displacement Prediction during the Sliding Process Using XGBoost, SVR and RNNs." Applied Sciences 12, no. 12 (2022): 6056.

[10] Collini, E., Palesi, L.I., Nesi, P., Pantaleo, G., Nocentini, N. and Rosi, A., 2022. Predicting and understanding landslide events with explainable AI. IEEE Access, 10, pp.31175-31189.

[11] Pradhan, Biswajeet, et al. "An explainable AI (XAI) model for landslide susceptibility modeling." Applied Soft Computing 142 (2023): 110324.

[12] Zhao, Chunhui, Xiaoqing Wan, Genping Zhao, Bing Cui, Wu Liu, and Bin Qi. "Spectral-spatial classification of hyperspectral imagery based on stacked sparse autoencoder and random forest." European journal of remote sensing 50, no. 1 (2017): 47-63.

[13] https://www.kaggle.com/datasets/adizafar/landslide-prediction-for-muzaffarabadpakistan

[14] https://data.world/datasets/landslide

[15] Gidon, J. Sharailin, Jintu Borah, Smrutirekha Sahoo, Shubhankar Majumdar, and Masahiro Fujita. "Bi-Directional LSTM Model for Accurate and Real-Time Landslide Detection: A Case Study in Mawiongrim, Meghalaya, India." IEEE Internet of Things Journal (2023).

[16] Knapič, Samanta, Avleen Malhi, Rohit Saluja, and Kary Främling. "Explainable artificial intelligence for human decision support system in the medical domain." Machine Learning and Knowledge Extraction 3, no. 3 (2021): 740-770.