EFFECT OF LANDSLIDES USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING PREDICTION MODELS

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ABSTRACT

According to data collected in India, landslides are geological hazards caused by the flow of rock, soil, and debris down a steep slope. Landslides in India are most commonly caused by snowfall, rain, and earthquakes. Certain climate conditions performance as landslide trigger points preventing socioeconomic loss. These trigger points must be monitored by machine learning techniques including artificial intelligence methods, which are most popular for modelling complex landslide problems and improving prediction over traditional methods. This article focused to ML and AI based landslide prediction methodologies, frameworks and models. In this research also suggests a prediction and Detection approach for to observe landslide occurrences and provide warning signs to intimate the resident people.

Keywords: Landslides, Machine Learning (ML), Artificial Intelligence (AI), Prediction Models

1. INTRODUCTION

Landslides are one of the most dangerous types of natural disasters in the world, causing destruction on human lives and the global economy. They effect almost 15% of India's land area and may be characterized in many ways. The occurrence of these phenomena is more pronounced in the youthful mountain ranges of India, such as the hilly areas, which are regularly impacted by the terrible occurrence of landslides, especially during the rainy season. Landslides are influenced by several climatic condition's intense rainfall, snowfall, and earthquakes are some of the climatic conditions. These are the indicators for landslides development. Landslides may result in significant economic and human damage. Thus, these climatic circumstances serve as a substance for landslides. To mitigate socioeconomic losses, it's crucial to monitor these trigger points. In current research, to reduce the losses by landslide prediction methods and models[1].

AI has been applied for landslide investigation, including detection, characterisation, susceptibility evaluation, prediction, and early warning systems. Previous research efforts used experienced data scientists executing algorithms on Machine Learning (ML) platforms[2]. Existing solutions are unsuitable for strategic decision makers with minimal expertise of machine learning and artificial intelligence. In our current study, we focused to ML and AI based landslide prediction method, frameworks and models.

- **Landslide Detection**

Rapid and accurate landslide detection is crucial for damage assessment and disaster management. It also improves disaster mitigation efficiency. Landslide detection involves recognizing possible landslides and analyzing their fine-scale patterns. Obtaining accurate and timely information on landslides is crucial, particularly during approach. Conducting field investigations on major landslides, particularly those that have just occurred, may be risky and challenging [3]. Conducting a field survey in a disaster region may be challenging due to dangers and the need for extensive resources. To prevent these problems, it is vital to use emerging approaches for autonomously identifying landslides. To detect landslides, event-based inventories should be generated as soon as possible. These inventories provide baseline information (e.g., landslide types, location, magnitude, distribution, and boundaries) and show the relationship between landslides and a single conditional factor [4]. Landslide inventories may help identify underlying causes and forecast future landslides.

- **Landslide Prediction**

Since landslides may result in a variety of risks, it is essential to anticipate them in order to minimize the loss of life and financial damages. To lessen the effects of landslides, landslide prediction must be done. A variety of processing methods and prediction models used for this study.

A Support Vector Machine (SVM)-based prediction model has been created in this study [5][11]. A machine learning algorithm called SVM is based on the statistical learning approach. Spatial and infrastructural datasets were created with the use of GIS technology, and the area's landslide contributing variables were identified. Prediction models would thus be dependent on affecting variables. With a short sample size, SVM provided us with a globally optimum solution with great accuracy. GIS provided the solution's visual representation. Even if this model provides a better answer, further study will be necessary to determine the specific parameters that this model requires in order to save time. Its efficiency will undoubtedly increase as a result. India is no longer an exception to the rule that landslides inflict enormous devastation around the globe. Large, rugged terrain that is characteristic of China's huge region has been impacted by landslides. According to there were devastating effects from the earthquake that occurred near these Indian territories [6]. Measures for machine learning-based landslide identification must be considered in order to prevent these problems. Color and texture paired with machine learning classification techniques and remote sensing imagery may assist identify landslide triggers. When compared to other algorithms like SVM, the Extreme Learning Machines (ELM) method takes the least amount of time. They demonstrated the outcome for the same using a statistical model and an image sensing technique [7]. The efficiency of this ELM method may be raised, and by reducing the number of hidden nodes, it can shorten the recognition time. Rainfall-induced landslides have resulted in significant economic and social losses in India. Scientists were prompted by these widespread losses to determine the various methods for anticipating landslides caused by rains [8].

2. LITERATURE REVIEW

Pham et al. [9], used a Machine Learning (ML) approach to analyze landslide susceptibility. They utilized a Convolutional Neural Network (CNN) together with a dedicated optimization method to find the most appropriate parameters. The study area of Lai Chau is a mountainous province in Vietnam. The dataset included 2374 points of landslides and randomly selected non-landslides. The dataset also included 12 area features: Elevation, Aspect, Slope, Stream Power Index (SPI), Compound Topographic Index (CTI), Curvature, NDWI, NDVI, Normalized Difference Build-up Index (NDBI), Distance to River, River Density, and Precipitation in the long term.The evaluation criteria that have been used include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Area under Receiver Operating Characteristics (AUC), and Overall Accuracy (OA). The suggested Convolutional Neural Network (CNN) architecture outperformed Random Subspace, Random Forest (RF), and CNN models that used the usual Adagrad optimizer. The overall accuracy (OA) attained by the new architecture was 80.105%.

Abraham et al. [10] used the SIGMA model to calculate landslide forecasts in the Idukki region of India. The researchers used rainfall data to partition the study region into four reference zones based on the topography diversity and the positioning of rain gauges. The dataset used spans from 2009 to 2018, with the most recent year being employed for the validation of the SIGMA model. The model achieved a mean Accuracy of 79.31% across the four sectors.

Haojie Wang, Limin Zhang, Kesheng Yin, Hongyu Luo, Jinhui Li,et al. [11] Landslide Prediction & detection is essential for risk assessment and mitigation. This research presents a unique machine-learning and deep-learning strategy for detecting natural-terrain landslides utilizing integrated geodatabases. First, landslide-related data are compiled, which includes topographic, geological, and rainfall data. Then, three integrated geodatabases are created: Recent Landslide Database (RecLD), Relict Landslide Database (RelLD), and Joint Landslide Database (JLD). Following that, five machine learning and deep learning techniques, including logistic regression (LR), support vector machine (SVM), random forest (RF), boosting approaches, and convolutional neural network (CNN), are applied and tested on each database. A case study in Lantau, Hong Kong, is carried out to show how the suggested strategy may be used. According to the case study findings, CNN obtains an identification accuracy of 92.5% on RecLD, outperforming other algorithms owing to its capabilities in feature extraction and multidimensional data processing. Boosting approaches rank second in terms of accuracy, followed by RF, LR, and SVM. Using machine learning and deep learning approaches, the proposed landslide identification method demonstrates exceptional resilience and tremendous promise in addressing the landslide identification issue.

3. METHODOLOGY

This technology will assist in predicting rainfall-induced landslides using this model and informing locals of the likelihood of landslide occurrence. Implementing this methodology would undoubtedly assist to reduce losses in high-rainfall locations such as Uttarakhand, Himachal Pradesh and other similar places in India[12].These variables include various activities such as construction activity, deforestation in steep regions and construction activities including by other factors. Based on a review of several prediction models in this study suggested a framework for predicting landslides more accurately shown in Fig. 1.

Figure 1: Framework of landslides predicting

- **Landslide Prediction Model-Equation and Formulas**
- **Entropy (E_L)**

Entropy is the prediction constant derived from the historical data analysis. Determine the Entropy to categorize the effects of landslides. Use the round-off scale to match the entropy (E_L) [13]. Determine the value of the entropy constant using the round-off scale.

$$\boxed{E_L \ \alpha \ (\text{Landslide Causes} * \text{Soil Structure})}$$

$$\boxed{\text{Landslide Causes} = (\text{Trigger} + \text{Economic Loss})}$$

The parameters utilized in the trigger scale and economic loss calculations are the results of the High-D tool that was applied to the dataset and analyzed. Trigger points in this situation will be the output obtained from High-D, such as an earthquake, which results in a great economic loss, followed by Earthquake,Rainfall, Flooding, Downpour and others show in Table 1.

Table 1: Parameters utilized in the trigger scale

Trigger	Scale	Economic Loss	Scale
Earthquake	5	Erosion	5
Rainfall	4	Ground water Change	4
Flooding	3	Evolution	3
Downpour	4	Material Properties loss.	4
Others	3	Others	3

- **Soil Structure**

Soil structure is another significant component that is consideration for analysis. In this study we have investigated two parameters, Soil Moisture Content and Soil Texture inside the soil structure. Therefore, soil structure is determined by two specific characteristics.

Soil Moisture + Soil Texture

- **Soil Scaling Ranges**

The soil scaling ranges are determined based on the strength of the soil slope.

- **Soil Moisture Content**

Calculating Soil Moisture Scaling in Table 2 with following content

Table 2: Range of soil moisture content

Soil Moisture Content(m^3)	Scale
0-15	1
15-25	2
25-35	3
35-45	4
45 and Above	5

- **Soil Texture Content**

Table 3 shows the scaling of soil texture content

Table 3: Shows the scaling of soil texture content

Soil Texture	Scale
1-3 Sandy Soil	5
2-6 Sandy Loamy soil	4
7-12 Clay Soil	3
13-14 Organic Material	2
15 Rock & Stone	1

- **Entropy Scale**

The graph divides areas into three danger groups based on the computed entropy scale show In Figure 2.

- High: 70-100
- Medium: 30-70
- Low: 0-30

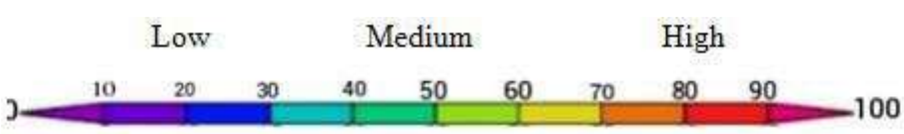

Figure 2: Entropy Scale

- **Entropy Risk Scale**

Table 4: Categories and scale

Categories	Scale
High	601-900

Medium	301-600
Low	0-300

- **Landslide Variable (L_v)**

The landslide prediction model uses this variable as a real-time input. Landslide Variables taken into consideration for our prediction model.

- Current rain
- Wind speed
- Humidity

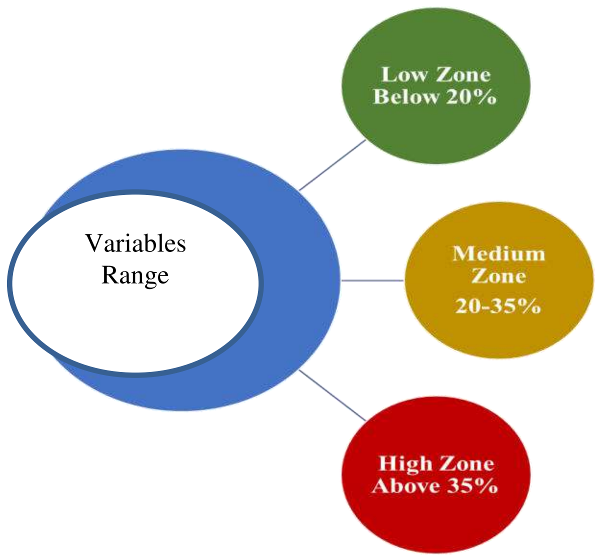

Figure 3: Landslide Variable Range scale with colour coding

Note- Green- Low Zone,Yellow-Medium Zone,Red-High Zone

- **Comparative Analysis Method**

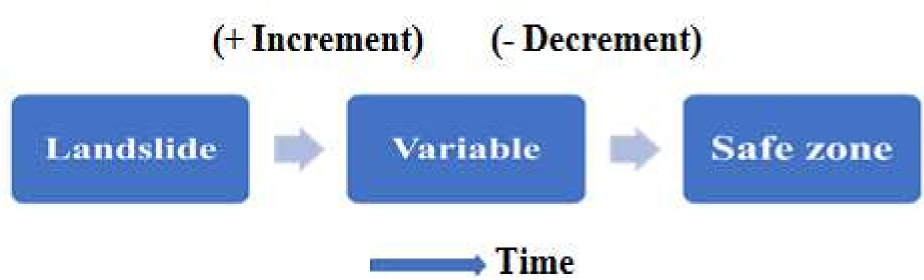

Figure 4: Changes of variables

Tendency of the changes in variables show in Figure 4 describe to the how many elements are moving in the direction of the following zones:

Landslide: When the factors continuously increase

Safe zone: When conditions remain stable (below the danger line) or gradually decrease

Note: The percentage of changes is computed using the reported deviation from the norm.

4. ANALYSIS AND RESULT

- **Categories Zone**

Table 5: Categories Zone

Categories	Range or Values (%)
High	Above 35
Medium	20-35
Low (Safe Zone)	Below 20

A. Low or Safe Zone:- The safe zone is formed when all of the variable are below 20%, as shown in Figure 5.

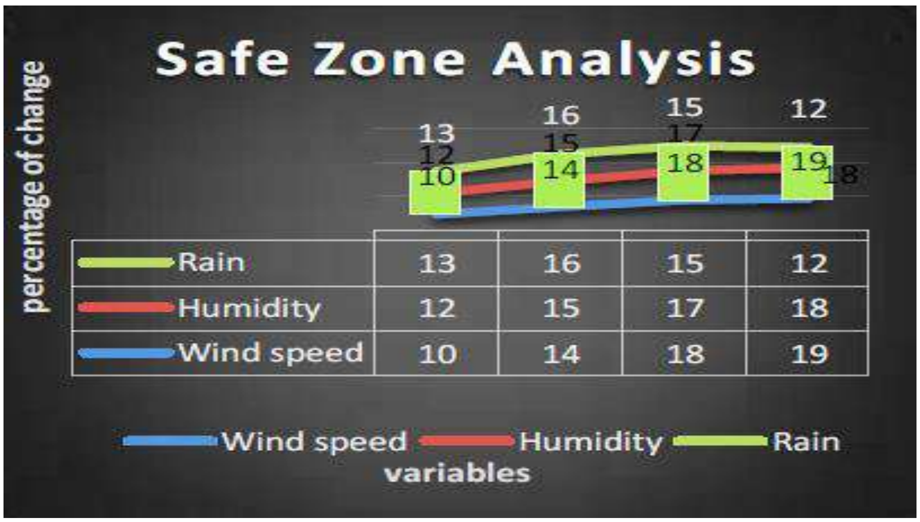

Figure 5: Analysis Result of Safe Zone variable range are below 20%

B. Medium Zone:- This range is split into two situations based on the factors that change when the environment changes.

- **If the variable range of wind speed and humidity changes 20%–35%**

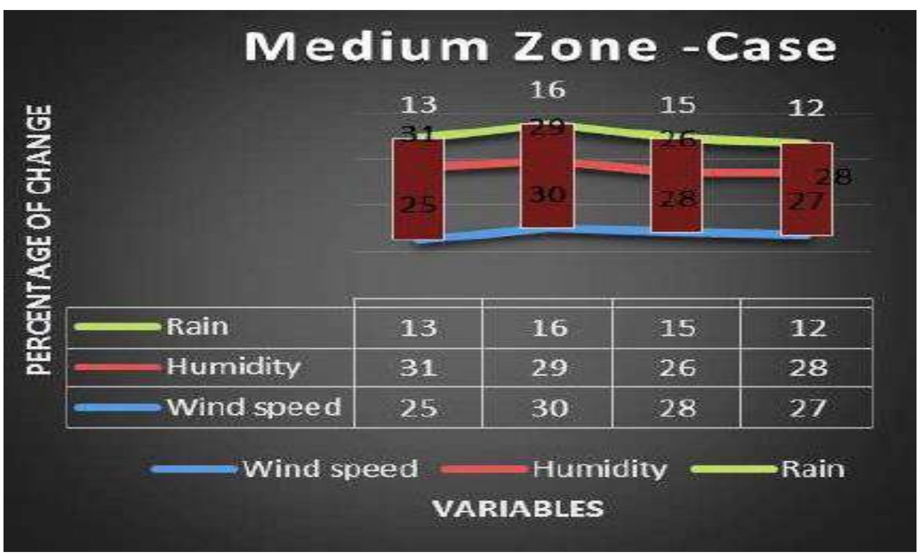

Figure 6: Analysis Result of Medium Zone wind speed and humidity change 20%–35%

- **If the variable range of rainfall recorded between 20% - 35%**

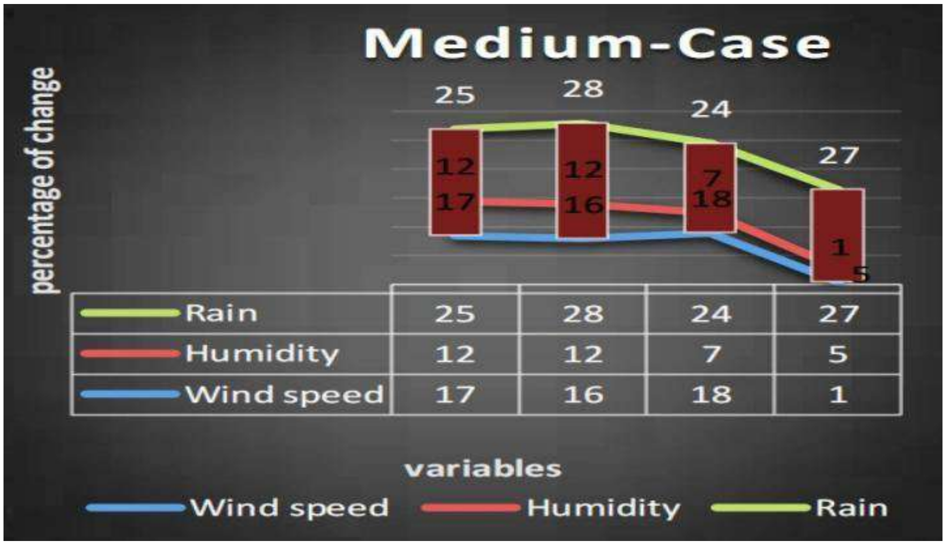

Figure 7: Analysis Result of Medium Zone the range of rainfall recorded between 20% - 35%

C. High Zone:- The high zone is formed when all of the one or all variable cross above 35% shown in Figure 8.

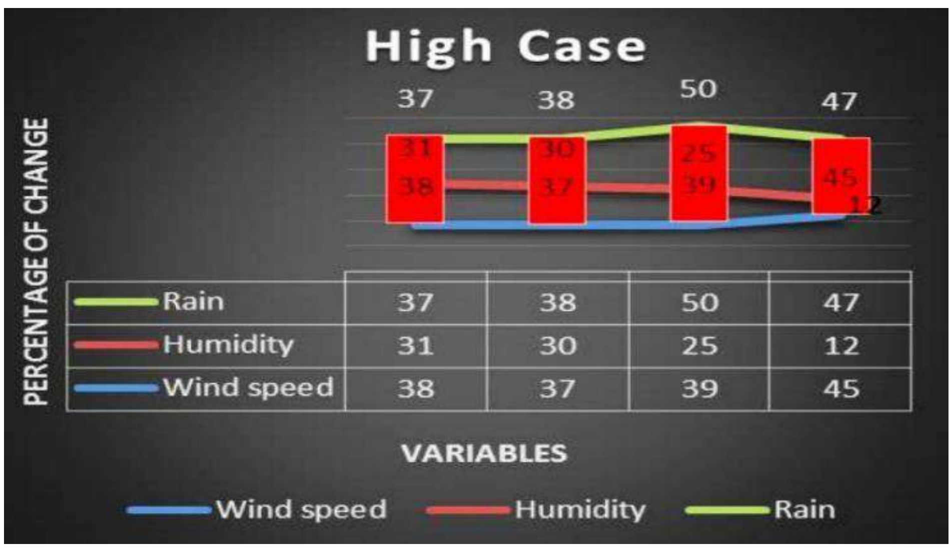

Figure 8: Analysis Result of High Zone variable range are above 35%

- **Landslide Prediction**

This is the variable calculated based on entropy and variables

$$LP = Entropy * \text{ Landslide variable}$$

- **Landslide Prediction Scale**

The visualization of the scale is given below in Figure 9.

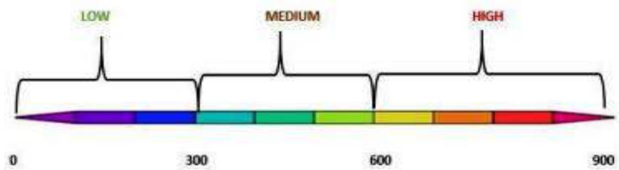

Figure 9: Landslide Prediction Scale

5. CONCLUSIONS

In this work, researchers evaluated data from India and discovered three trigger points: snowfall, rainfall, and earthquake. Furthermore, based on the existing literature, we created a prediction model, comprising an equation and a warning system, to emphasize the occurrence of landslides. This technique may be improved in the future by including artificial intelligence and machine learning, which allows for more accurate analysis of landslide occurrences.In the future, researchers may use the suggested prediction model to real-time landslide prediction. Another key feature to consider is slope stability, which will make the prediction model more accurate in terms of finding.

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