Landslide Susceptibility Mapping Using Machine Learning Approach: A Case Study of Baglung District, Nepal

Ashish Chalise, Bipin Sinjali, Tejendra Kandel, Janak Parajuli, Sanjeevan Shrestha
ashish.chalise5@gmail.com, bipinsinjali@gmail.com, tejendra160@gmail.com, janak.paarjuli1@gmail.com, shr.sanjeevan@gmail.com

KEYWORDS

Landslide Susceptibility, Random Forest, Frequency Ratio, Classification and Regression Tree, Area Under Curve

ABSTRACT

Assessment of Landslide Susceptibility Map (LSM) is crucial to the reduction of risk of the landslides. This paper focusses on modelling LSM using two different machine learning algorithms namely Random Forest (RF), and Classification and Regression Tree (CART). Ten landslide causative factors along with an inventory of landslides containing 89 recent and historic landslide points, and 90 randomly generated non-landslide points were used to prepare a susceptibility map. The study area; Baglung district is located in the Gandaki province of Nepal, a highly landslide susceptible zone. Frequency ratio (FR) of each class of conditioning factors were calculated. FR values of landslide and non-landslide points were extracted from normalized FR classified raster. The extracted FR values of each point (landslide and non-landslide) was randomly split into training (70%) and testing (30%) samples which were used for training and testing the model. The performance of each algorithm was evaluated using receiver operating characteristics (ROC) curves in combination with area under the curve (AUC) and error matrix. The AUC results introduced success rate of 1 and 0.88 for RF and CART respectively. Also, the rates of prediction were 0.86 and 0.96 for RF and CART respectively. Similarly, RF and CART showed accuracy of 0.88 and 0.83 from confusion matrix. Therefore, the RF algorithm was superior to CART in identifying the regions at risk for future landslides in the study area. The outcomes of this study is useful and essential for the government, planners, researchers, decision makers and general land-use planners.

1. INTRODUCTION

The movement of rocks, soil, earth or debris of the sloped area due to the unstable slope of the land is known as landslide. Landslides can cause, or occur due to various factors i.e., earthquakes, rainfall, soil type, climate change, geological, hydrological, geomorphological conditions, and other geographic. Landslide is caused by variety of natural process that triggers the movement of earth materials from slow to rapid downslope (Health, 2020). Every country in the world is facing landslide as a major natural disaster. The top five countries with the highest risk of landslides are Italy, Austria, China, The Philippines, and Ethiopia with more than 7500, 6000, 5600, 4800,4800 square miles respectively (Watch, 2021).

Likewise, dozens of natural hazards and human induced disasters have been exposed in Nepal. Every year thousands of people have lost their lives and millions of properties have been damaged due to landslides occurring around the Nepal (Portal, 2021). Thus, major incidents for death are flood, landslide, thunderbolt, fire, cold wave, high altitude and heavy rainfall (Affairs, 2019). Nepal Disaster Risk Reduction Portal data 2021 shows, 2386 landslides incidents has occurred in Nepal in a decade time period (2010-2020) thus leading to third highest natural disaster incidents in the country (Portal, 2021). Landslides is one of the very common natural hazards in the hilly region of Nepal. In Nepal, where two third of the total area falls in hilly and mountainous region, landslides represent a major constraint on development, causing high levels of economic loss and substantial numbers of fatalities. Each year rugged and stepped topography, unstable geological structures, soft and fragile rocks, along with concentrated and prolonged heavy rainfalls during monsoon periods collectively cause severe land sliding and related phenomena in the mountainous part of Nepal (Acharya, 2018). To overcome these problems, landslide susceptibility model can play a crucial role in determining the most vulnerable landslide areas (Mersha & Meten, 2020). Susceptibility models are very useful to represent the likelihood of a landslide occurring in any specific location in terms of relative probability (Pradhan, 2010). Landslide inventories containing data on the factors that causes landslide, can be used to model landslide susceptibility which can be used to predict future landslide occurrences and their characteristics.

There are many approaches for predicting landslide prone areas. Some of them include frequency ratio, Shannon entropy, analytical hierarchal approach etc. However, machine learning approaches are effectual and more accurate approaches to develop landslide susceptibility model (Pham & Prakash, 2018).

Machine learning (ML) is a method of data analysis that automates and gives computers the capability to learn without being explicitly programmed (Li, 2021). It has been used in many applications such as urban growth monitoring (Shrestha S. , 2019), image classification (David N., 2021) , agriculture land classification and yield estimation (Fernandez-Beltran, 2021), building extraction (Shrestha S. V., 2018) etc. The main advantages of using ML methods in landslide mapping is for its analysis for the contributing factors for landslide development and their potential for continuous updating (Youssef & Pourghasemi, 2021). Two machine learning algorithms were used for this research namely CART and RF.

CART is a machine learning with classification and prediction tree model. The model would be appropriate to use for decision tree making with the classification and prediction model. Further explanation, the CART term is used to describe decision tree algorithms that are used for classification and regression learning tasks (Ninja, 2021). Thus, to explain the CART we have to understand the classification and regression decision tree individually; (i) Classification tree: Basically, classification decision tree is used to classify the datasets into multiple groups. Alternatively, the process of splitting the datasets into classes according to its response variable (homogeneity). i.e.; training and test dataset. (ii) Regression tree: It process of predicting the problems with response to the continuous variable (Prakash, 2018) . Its main task is to split the datasets for each independent variable by fitting the target variable by using the independent variables.

RF classification, which was originally developed by Breiman, is a machine learning algorithm for nonparametric multivariate classification (Catani, 2013). RF is a popular machine learning method that is widely used for classification and regression. Generally, a single decision tree individually exhibits weak prediction performance because of a high variance or bias (Taalab, 2018). RF creates numerous decision trees for classification which can also be perceived as a group of random decision trees. Therefore, RF is a combination of individually created decision trees to form a decision forest. Each tree in the forest has independent and identical distribution and thus, they are relatively uncorrelated with each other. The property that makes the RF, far from the overtaking risk. The results obtained from all decision trees are combined to obtain the result of the RF.

Nepal being prone to landslides during monsoon, he Nepal Disaster Risk Reduction Portal, 2021 shows that, Baglung district has recorded the highest number of landslides incidents in the past decade (Portal, 2021). So in this context, the paper tries to compare different machine learning algorithm for the preparation of land susceptibility map.

1.1 Objectives

The primary objective of this study area is to prepare landslide susceptibility map using ML algorithms and compare the accuracy results how it would vary accordingly.

The secondary objectives of this study are as follows:

- To prepare a landslide inventory map of Baglung district.
- To determine which landslide conditioning factor plays major and minor role in the occurrence of landslides within the study area.

1.2 Rationale of the Work

There have been many studies of landslide susceptibility mapping based on analytical and statistical methods but there are less studies in which machine learning algorithms are used. This study combines statistical method with machine learning algorithms to analyze its effectiveness for landslide susceptibility mapping and comparing the accuracy of both RF and CART models would also allow us to know the performance of each model.

This research can be very effective as landslide susceptibility map could help to minimize property loss, human lives and management of landslides. This study also helps in knowing what are the major and minor factors causing landslide within the study area.

2. STUDY AREA

Baglung district lies in the Gandaki province of western Nepal covering 1837 sq. km. Geologically, it lies on the Himalayan range of Nepal. The Nepal Disaster Risk Reduction Portal, 2021 shows that, Baglung district has recorded the highest number of landslides incidents in the past decade (Portal, 2021). Figure 1 represents the study area at a scale of 1:400000

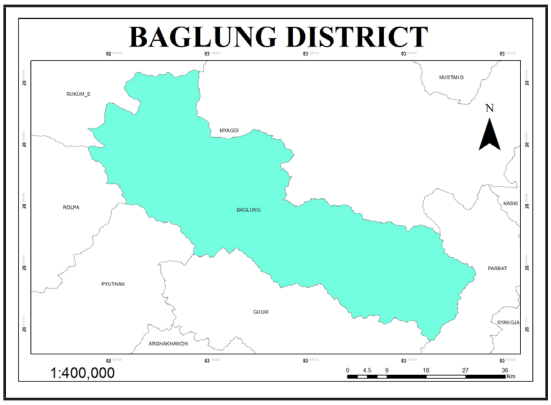

Figure 1: Study Area

3. MATERIALS AND METHODS

The research examines probable areas within the study area using landslide inventory and landslide conditioning factors. To obtain the LSM, the methodology (Figure 2) followed these major processing steps: data collection, reclassification of landslide factors, and calculation of relative frequency ratio of each factor variable, model development, model verification and preparation of the LSM.

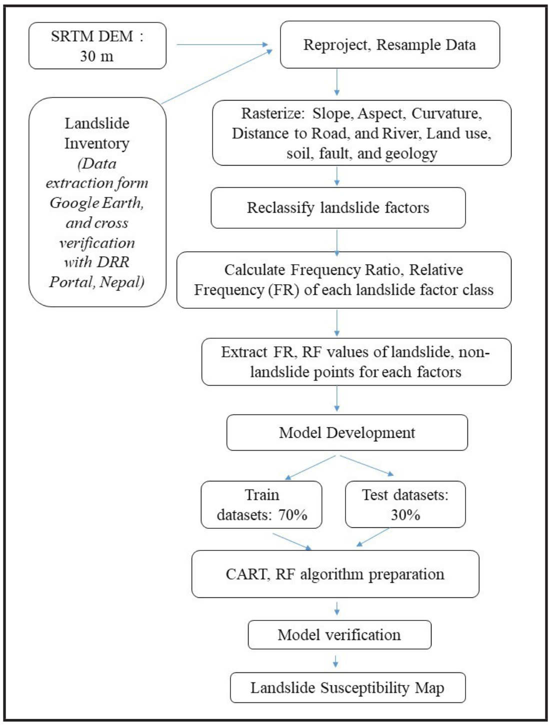

Figure 2: Methodology for the Preparation of Landslide Susceptibility Map.

3.1 Data and Software

Table 1 and Table 2 present the landslide causing factors considered and the software used for our research respectively.

Table 1: Landslide conditioning factor used in the study

S. N	Landslide Factors	Data Source
1	Distance to River	ICIMOD Portal
2	Distance to Road	ICIMOD Portal
3	Distance to Fault	ICIMOD Portal
4	Land use	ICIMOD portal
5	Geology	ICIMOD portal
6	Soil	ICIMOD portal
7	DEM (slope, curvature, elevation, aspect)	USGS (Earth Explorer)

Table 2: Software Used

S.N	Software	Usage
1	Google Earth	Sample Collection
2	R Studio	Analysis and modelling
3	GIS software	Visualization

Landslide Inventory: A total of 89 landslide points and 90 randomly generated non-landslide points were taken to create a landslide inventory, for the purpose of preparing binary class for landslide susceptibility mapping. For the training the classifier/algorithm, the generated points were furthered classified into training (70%) and testing (30%) data for our study.

3.2 Landslide Causative Factors

There are no fixed guidelines for selecting the parameters that influence landslides in susceptibility mapping (Carrara & Cardinali, 1991). The causative factors were selected based on previous landslide studies (Pradhan & Lee, 2010), (Youssef & Pourghasemi, 2021), (Catani, 2013), (Wang, Fang, & Hong, 2019), (Yilmaz, 2009), (Mersha & Meten, 2020), (Hawas, 2019), the scale of analysis, data availability and fieldwork in Baglung district. The most significant landslide-related data namely slope, elevation, aspect, curvature, geology, soil, land use, distance to river, distance to road, distance to fault were selected for this study area.

3.2.1 Preparation of Landslide Causative Factors.

The slope angle, aspect, curvature derived from 30 m DEM were extracted using package raster in R studio. Similarly, rivers, road, fault, geology, soil and land use data were obtained from the Database of ICIMOD. The layers of distance to streams, fault line, road was calculated by buffering R studio. Since remaining factors geology, soil, land use were continuous data so the data were kept raw. All data were converted to raster format with the same pixel resolution as DEM and each raster map was divided into several classes.

The following are the landslide causative factor used in this study:

a. **Slope**

The slope map does play crucial role to

develop landslide susceptibility because it is directly related to slope angle. The steeper the slope, the greater the landslide probability (Lee & Min, 2001). In this study, Slope Map was classified into 6 classes and number of landslide pixel in each pixel was calculated where highest number of landslides point with 43 in the class of slope angle 40-55 degree.

b. Aspect

Aspect is another important factor in the preparation of LSM. It is also connected with various factors like exposure to sunlight, drying winds, rainfall, and discontinuities that may affect the occurrence of landslides (Carrara & Cardinali, 1991). Aspect map was classified into eight classes where southern part was given the highest number of landslides point 30.

c. Curvature

Curvature is another commonly used parameter in landslide hazard analysis. Curvature can be subdivided into regions of concave outward plan curvature called hollows, convex outward plan curvature called noses, and straight contours called planar regions. Also, hollows have a slightly higher probability for landslides than noses (Gregory & Ohlmacher, 2006). Curvature map was classified into 3 classes namely concave, flat and convex where concave had the highest number of landslides with 52.

d. Elevation

Elevation map helps to determine the minimum and maximum heights of landslide occurrence within the ROI. Elevation map ranged between 580m to 4682m and was classified into 8 classes where maximum number of landslides 35 was assigned for class 1600-2100m.

e. Land use/Land cover

It is important to know which area of land cover has higher number of landslide and low or no landslide (Sivakami, 2014). Land use map with 8 classes was prepared where agriculture area had the highest number of landslide frequency with 44 followed by forest area with 22.

f. Geology

Geology plays an important role in landslide susceptibility studies because geological units have different susceptibilities to active geomorphological processes of the area (Pradhan, 2010). The study area was covered by 10 geological formations with highest number of landslide points 22 within lakharpata formation.

g. Soil

Land cover with different soil characteristics has diverse effects in the occurrence of landslides. It does not only affect the development degree of landslides in the areas, but also determines the type and scale of landslide (XIanyu Yu, 2021). The soil of study area was classified into 4 types in which 46 landslide point were within soil type of Dystrochrepts, Halpumbrepts, Haplustalfs-calcarious soil Materials.

h. Distance to River

The distance to river map showed the buffer zones with seven different classes. It does not affect in the occurrence of landslides directly. Despite that, the proximity of the slope to the drainage structures is important factor in terms of stability because it may affect stability of slopes or by saturating the lower part of material until the water level increase (Sivakami, 2014). More than 60 landslides occurred in buffer distance of 400 m.

i. Distance to Road

Landslides are very common along road cuts. This is mainly due to the damage in the natural condition of the slope during road construction. Also, the road cut exposes the joints and fractures that make the slope unstable. Road cuts are usually sites of anthropological instability (Pradhan, 2010). The distance to road map was prepared with 7 classes where

58 landslide points occurred in buffer zone of more than 450 m from highways.

j. Distance to Fault

The study area contained only one fault line where almost all landslides point were found on buffer zone of more than 450 m from the fault line.

3.3 Determination of Frequency Ratio

Frequency ratio is a quantitative technique for landslide susceptibility assessment using spatial data (Lee & Min, 2001). It is frequently and effectively used for landslide susceptibility mapping. As it is quantitative method so it quantifies between the landslide inventory and causative factors. (Hawas, 2019). The frequency ratio was calculated for each class of causative factors type or range were calculated from their relationship with landslide occurrence. Likewise, the ratio was calculated for sub criteria of parameter. The Frequency Ratio of each class were calculated with the following formula.

$$FR = (Mi/M)/(Ni/N), \qquad (1)$$

where,

Mi= The number of pixels with landslides for each subclass conditioning factor,

M= The total number of landslides in the study area,

Ni= The number of pixels in the subclass area of each factor,

N= The number of total pixels in the study area.

Relative Frequency: FR of class / sum total of all FR value in that factor.

The relative frequency is calculated to normalize FR value within 0 to 1.

Relative frequency of each factor class was calculated. The classified raster was again reclassified with RF values. The rf value of each landslide and non-landslide point for each landslide conditioning factor was extracted later which was used as training and testing data set for model preparation using machine learning algorithms.

3.4 Model Development

The following ML algorithms were used to develop landslide susceptibility model which were further used to prepare landslide susceptibility map.

3.4.1 Classification and Regression Tree (CART)

The pre-processed and modelled data were carried out for the final stage of the landslide susceptibility. CART decision tree was used to classify and run the regression among the data.

Thus, in the classification, the data was split into training and test datasets within 70% -30% ratio respectively. The assigned percentage of the datasets were used to fit in model. Now, making a decision tree using R where, landslide/non-landslide point was used as dependent variable in the training datasets, and other variable as independent variables. Then, class method was used to classify the datasets. CART Package available in R was used to use CART algorithm to prepare a susceptibility model from the training dataset. Thus, the importance value of each factor variable from model was taken and multiplied with respective factor variable raster to create landslide susceptibility map. Not only that prediction of outcome on the test dataset, was done and predicted those classes into either 0 or 1, 0 as non-landslide and 1 as landslide.

3.4.2 Random Forest

Similar to CART random forest algorithm was also used to prepare a model from training dataset. The package in R was used to use random forest algorithm to prepare a landslide susceptibility model from the training dataset available. Thus, the importance value of each factor variable from model was taken and multiplied with respective factor variable raster to create landslide susceptibility map.

Also, the model was used on test data set to check the accuracy of the model.

3.5 Accuracy Assessment

Accuracy assessment of model from CART and random forest algorithm was performed using test data set. Two accuracy assessment methods namely confusion matrix and Area Under Curve (AUC) was used to check the accuracy of the both models.

To check the performance of the model Receiver Operator Characteristics (ROC) curve was used as accuracy assessment method. Area Under Curve AUC is calculated for multiple logistic regression models because it allows us to see which model is best at making predictions. The interpretation of the ROC curves moves to the top left corner of the plot, thus in this category it does better accuracy or it does better classification of the data. Likewise, the AUC is calculated to quantify and tells us how much of the plot is located under the curve. Thus, we can say, closer of AUC to 1, the better the model. Moving toward the graph representation, the ROC curve places the True Positive Rate (Sensitivity) in the Y-axis, and on the X-axis, it will be the False Positive Rate (1- specificity). The prediction and success rate curve were also developed from the test and train datasets respectively.

Confusion matrix is another way to evaluate the performance of the model. Confusion matrix from the test data set was obtained and overall accuracy was derived. Overall accuracy is the probability that an individual will be correctly classified by a test, i.e., the sum of the true positives plus true negatives divided by the total number of individual tested.

4. RESULT AND DISCUSSION

The final landslide susceptibility map was prepared by multiplying landslide causative factor with the importance value of each factor given by both the model. The final map is classified into four groups (i.e., Low, Medium, High, Very High) to see the susceptibility level from both the model.

The final Landslide susceptibility map by using random forest algorithm was generated using equation 2 where each factor is multiplied by its respective weight. The weight of each factor is calculated by running training dataset on random forest algorithm.

$$Model = river*0.22364691 + road*0.41075731 + fault*0.08207446 + geology*0.38538238 + soil*0.41437370 + elevation*0.55454643 + landuse*0.84776509 + slope*1.42814362 + aspect*1.40435311 + curvature*0.30321441 \quad (2)$$

The final map from Random Forest method is shown in figure 3 as below:

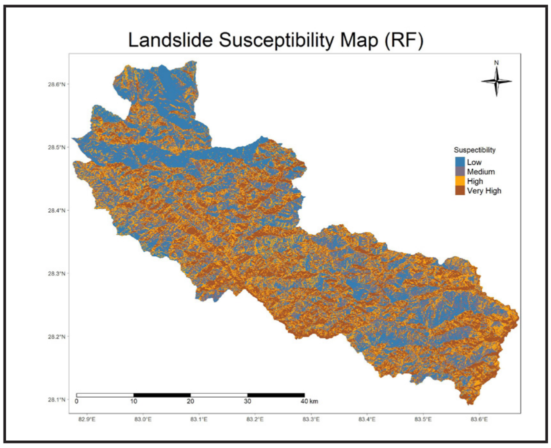

Figure 3: Landslide Susceptibility Map using Random Forest Model

The final Landslide susceptibility map by using CART algorithm was generated using equation 3 similar to method RF as mentioned earlier.

$$Model = river*0.3157572 + road*0.7556933 + fault*0.1294887 + geology*0.0381617 + soil*0.4016218 + elevation*0.1241790 + landuse*0.3923891 + slope*1.6985024 + aspect*1.2517241 + curvature*0.1908085 \quad (3)$$

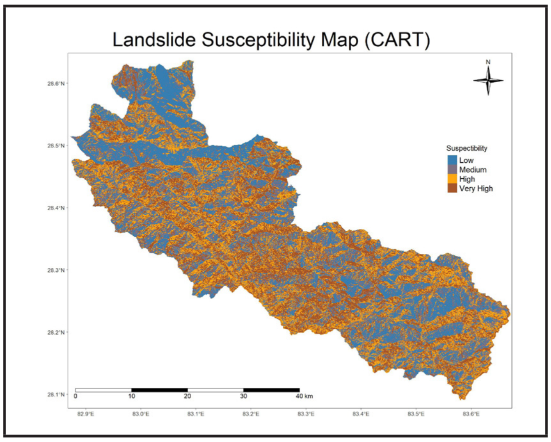

Figure 4: Landslide Susceptibility Map using CART Algorithm

The landslide susceptibility map from CART shows that almost 24.44 % and 17.83% of the total Baglung is susceptible to high and very high-risk zones. Similarly, the landslide susceptibility map from RF shows that almost 30.41% and 17.64% of the total area is susceptible to high and very high-risk zones. From both the model it can be seen that more that 40% of the total area is susceptible to landslide risk.

In RF model using test dataset to check the accuracy of the model the confusion matrix showed an overall accuracy of 88%. Similarly, two ROC curves namely prediction rate curve (figure 5) using test dataset and success rate curve (figure 6) using training dataset was generated and AUC was calculated which showed an AUC of 0.96 and 1 on PRC and SRC respectively.

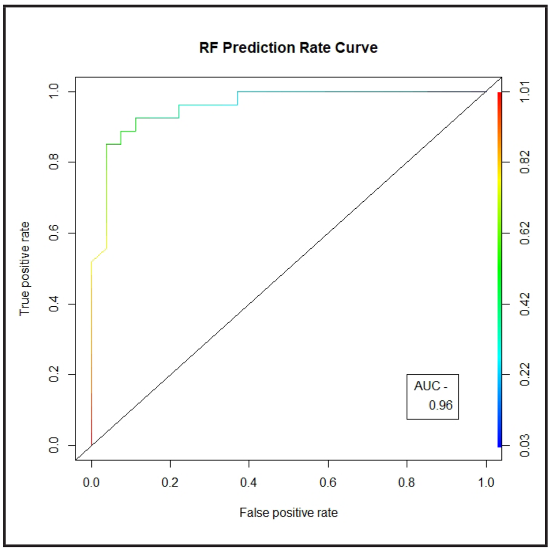

Figure 5: Prediction Rate Curve (RF)

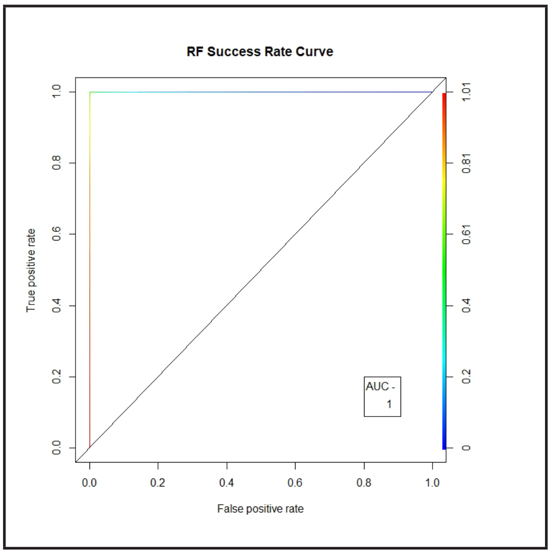

Figure 6: Success Rate Curve (RF)

In CART model using test dataset to check the accuracy of the model the confusion matrix showed an overall accuracy of 83%. Similarly, two ROC curves namely prediction rate curve (figure 7) using test dataset and success rate curve (figure 8) using training dataset was generated and AUC was calculated which showed an AUC of 0.86 and 0.87 on PRC and SRC respectively.

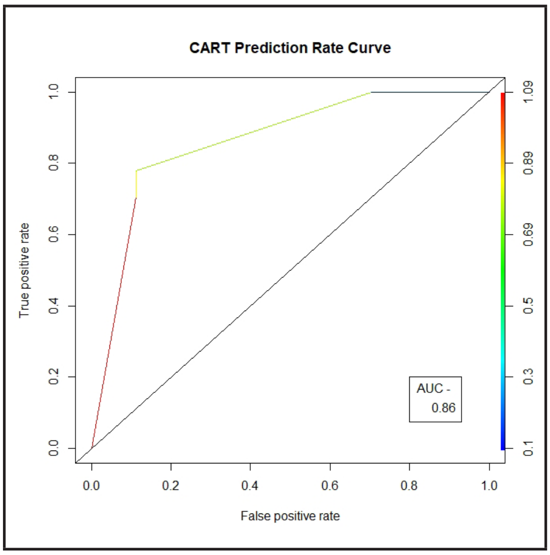

Figure 7: Prediction Rate Curve (CART)

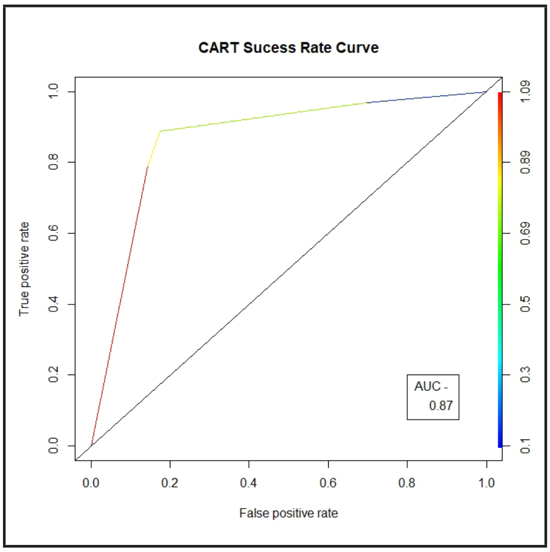

Figure 8: Success Rate Curve (CART)

The accuracy assessment obtained from test data set (30%) using AUC method shows Random Forest model in comparison to CART algorithm performs better as the accuracy assessment shows 88 % and 96% accuracy from CART and RF respectively. The main reason behind the more accuracy from random forest model can be that its randomized feature selection method. Unlike CART algorithm which depends specially on a feature and then creates child trees, the RF algorithm randomly selects a feature which makes this method more accurate than the other.

5. CONCLUSION

This paper focuses on predicting landslide susceptible zones with in Baglung district using two algorithms RF, CART and assess the accuracy of both models.

The accuracy obtained from RF algorithm is better than the accuracy obtained from CART algorithm. For a better landslide susceptibility results high accurate data is preferred. Since more than 40% of the total area is susceptible to landslide risk it can be concluded that Baglung district is one of the most risk prone area for landslide. Also, machine learning algorithms can be effective methods for landslide susceptibility analysis with RF being more accurate than the CART.

REFERENCES

Acharya, T. D. (2018). Regional Scale Landslide Hazard Assessment using Machine Learning Methods in Nepal.

GoN (2019). Nepal Disater Report. Kathmandu, Nepal: Ministry of Home Affairs, Government of Nepal.

Carrara, A., & Cardinali, M. D. (1991). *GIS Techniques and Statistical Models in Evaluating Landslide Hazard.* Earth Surface Processes and Landforms.

Catani, F. L. (2013). Landslide Susceptibility Estimation by Random Forests. *Natural Hazards Earth System*, 2815–2831.

Nhemaphuki, D., Chhetry, K. T. & Shrestha, S. (2021). Fusion of Radar and Optical Data for Land Cover Classification Using Machine Learning Approach. *Journal of Geoinformatics, Nepal*, 39-45.

Fernandez-Beltran, R. B. (2021). Rice-yield Prediction with Multi-temporal Sentinel-2 Data and 3D CNN: A case Study in Nepal. *Remote Sensing*, 1391.

Gregory, C., & Ohlmacher. (2006). *Plan Curvature and Landslide Probability in Regions Dominated by Earth Flows and*

Earth Slides. USA: Elsevier.

Hawas, K. M. (2019). *Landslide Susceptibility Assessment Using Frequency Ratio, a Case Study of Northern Pakistan.* Pakistan: ScienceDirect.

Health, E. R. (2020). Landslide Susceptibility Mapping Using Machine Learning.

Lee, S., & Min, K. (2001). *Statistical Analysis of Landslide Susceptibility at Yongin.* Korea.

Li, H. (2021). *Machine Learning: What it is and Why it Matters.* Retrieved from https://www.sas.com/en_us/insights/analytics/machine-learning.html

Mersha, T., & Meten, M. (2020). GIS-based Landslide Susceptibility Mapping and Assessment Using Bivariate Statistical Methods in Simada area, Northwestern Ethiopia. *Geoenvironmental Disasters 7*, 20.

Ninja. (2021). *Classification & Regression Trees*. Retrieved from https://www.codingninjas.com/blog/2020/12/02/what-is-classification-regression-trees/

Pham, B., & Prakash, I. (2018). Spatial Prediction of Landslides Using a Hybrid Machine Learning Approach Based on Random Subspace and Classification and Regression Trees. *Geomorphology*, 303.

Portal, N. D. (2021). *Reported Number of Incidents.* Kathamandu, Nepal: Nepal Diaster Risk Reduction Portal.

Pradhan, B. (2010). Landslide Susceptibility Mapping of a Catchment Area Using Frequency Ratio, Fuzzy Logic and Multivariate Logistic Regression Approaches. *Journal of the Indian Society of Remote Sensing*, 301-320.

Pradhan, B., & Lee, S. (2010). Landslide Susceptibility Assessment and Factor Effect Analysis: Back Propagation Artificial. *Environ. Model. Softw.*, 747-759.

Pradhan, B., & Lee, S. (2010). Landslide Susceptibility Assessment and Factor Effect Analysis: Backpropagation Artificial Neural Networks and Their Comparision With Frequency Ratio and Bivariate Logistic Regression Modelling. *Environmental Modelling Software*, 747-759.

Prakash, I. (2018). Machine Learning Methods of Kernel Logistic Regression and Classification and Regression Trees for Landslide Susceptibility Assessment at Part of Himalayan Area, India. *Indian Journal of Science and Technology*, 1-10.

Shrestha, S. (2019). Spatio-Temporal Analysis and Modeling of Urban Growth of Biratnagar City, Nepal. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 97-102.

Shrestha, S. V. (2018). Improved Fully Convolutional Network With Conditional Random Field For Building Extraction. *Remote Sensing*, 1135.

Sivakami, C. S. (2014). *Landslide Susceptibility Zone Using FR Model.* IISTE.

Taalab, K. T. (2018). Mapping Landslide Susceptibility and Types Using Random Forest. *Big Earth Data*, 159-178.

Wang, Y., Fang, Z., & Hong, H. (2019). Comparison of Convolutional Neural Networks for Landslide Susceptibility Mapping in Yanshan County, China. *Sci. Total Environ*, 975-993.

Watch, R. (2021). The List of Countries at High Risk of Landslides. . In *Retrieved from watch: https://blog.resourcewatch.org/2018/08/27/italy-austria-and-china-top-the-list-of-countries-at-high-risk-of-landslides-right-now/.*

XIanyu Yu, K. Z. (2021). *Study On Landslide Susceptibility Mapping Bases On Rock-Soil Characteristics Factors.* Scientific Reports.

Yilmaz, I. (2009). Landslide Susceptibility Mapping Using Frequency Ratio, Logistic Regression, Artificial Neural Networks And Their Comparison: A Case Study From Kat Landslides(Tokat- Turkey). *Comput. Geosci.*, 1125-1138.

Youssef, A. M., & Pourghasemi, H. R. (2021). Landslide Susceptibility Mapping Using Machine Learning Algorithms and Comparison of their Performance at Abha Basin, Asir Region, Saudi Arabia. *Geoscience Frontiers*, 639-655.

Author's Information

Name	:	Ashish Chalise
Academic Qualification	:	BE in Geomatics Engineering
Organization	:	CTEVT
Designation	:	Instructor
Work Experience	:	2 Year
Published Paper/Article	:	2
Email	:	ashish.chalise5@gmail.com