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Classification of Landslides Using Artificial Neural Networks

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Abstract
A landslide is a sudden collapse of a part of an inclined land which causes lots of damage to human lives and property. It usually happens in hilly areas due to geographical anomalies and especially during the rainy seasons where there will be heavy rains. Many scientists conducted research on why landslides occur and how they can be prevented. Many works have been proposed in which machine learning is used to identify the landslide. But it is also important to identify the type of landslides. Our work focuses on classifying the type of landslide. We use an Artificial Neural network and categorize the type of landslides into Small, Medium and Large based on six attributes present in the dataset. SMOTE algorithm was used to balance the imbalanced input dataset. Our model achieved 75% accuracy in identifying the type of landslide.

Keywords: Artificial Neural Network, SMOTE, Landslide detection, Machine Learning

Introduction

Landslides or slope failure is a condition which majorly occurs in the regions which are at a certain elevation from the ground in which a piece of land disintegrates and moves downwards at great speeds which often causes damage to human lives and property.

There are many reasons which cause a piece of land to slide. An earthquake or sudden movements in the tectonic plates can readily trigger a landslide. Rain is the secondary reason for a landslide as it erodes the soil and makes the land weak, thus causing a slope failure.

Steeper the slope, more the area is prone to the landslide. Modern farming methods which are being practiced on the slopes may also make the soil weak and cause a landslide. Cutting the trees on the slopes for farming and burning that farm after using causes the soil to weaken. Slopes with good vegetation are less prone to landslides. Very loud sounds may also cause a landslide because they make the land tremble. Storing large amounts of water on top of slopes without proper storage facilities may cause water leakage and the resultant wet land might slide off causing a landslide. The number of landslides has been rapidly increasing since the usage of modern technology to build roads and dams in the hilly regions. Using bombs to blast off the land for such purposes will heavily damage the slope region.

If we consider all the above things, it can be said that a system which identifies and classifies the landslide is the need of the hour. Therefore, we propose a Artificial Neural Network based model which classifies the type of the landslide into three classes viz Small, Medium and Large. We used the landslide dataset to train our model and it's working is explained in the further sections.

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Following this section is the Related work, Working and Results. In the final section we have given some concluding remarks.

Related Work

The authors in [11] proposed a framework to recognize avalanches on hyperspectral images. The framework comprised of a deep belief network which will be utilized to remove the spectral spatial highlights of a landslide followed by a logistic regression classifier for checking the landslide. The accuracy of their system was found to be 97.91%. They additionally expressed that their high-level feature extraction framework has a huge potential for slope failure identification. The authors in [15] constructed a database using 4069 historical landslide locations in Iran and 11 conditioning factors. They were used to generate maps of the regions which are more prone to landslides. RNN was found to be better than CNN with AUC of 0.88 when compared to CNN which was 0.85. From the output of the model, it was inferred that 20% of the land spaces of Iran are highly or very highly prone to slope failures. It was also found that 31% of urban communities are situated in regions with high or extremely high vulnerability of a landslide. Slantness, topography, land use and distance from the faultlines are the best factors to determine landslide events in Iran.

Bivariate statistical-based kernel logistic regression (KLR) models were used by authors in [13]. Different kernel functions, namely PLKLR, PUKLR, and RBFKLR models, were used for evaluating the proneness of an area to a landslide. The authors in [14] used different Machine learning ensemble frameworks and compared them for the checking the susceptibility of landslides for places present in the Himalayas in India. AdaBoost, Bagging, Dagging, MultiBoost, Rotation Forest, and Random SubSpace were used with the base classifier as a MLP neural network. MultiBoost was found to be the most effective ensemble with and AUC of 0.886 when evaluated using receiver operating characteristic curve and Chi Square test methods.

Another novel method for landslide identification was presented by the authors in [12]. By making the use of geodatabases by compiling lanslide, topographic and geological and rainfall related data they prepared three geo databases and trained machine learning algorithms like SVM, CNN, RF, LR and used boosting method. CNN was found to be the best amongst all of these with an accuracy of 92.5%.

Working Methodolgy

The project can be divided into two primary parts whose description is given below:

Data Pre-Processing:

The dataset contained columns of data. It was found that the columns 16 columns like event information, location information depending fields were necessary to determine the output, hence those were deleted. NaN value rows were deleted in Landslide_trigger field because these values were not used in training.

Size of Landslide field values are categorized into 6. among those catastrophic and unknown value rows very low leads to more variations in results, hence ignored the rows with field values catastrophic and unknown. large category and very large category were combined in to single field value as large. after preprocessing of data only three values are Large, small and medium.

The input for landslide detection is based on 6 fields I.e when the event is triggered, and its category and output is the size of the landslide.

SMOTE approach is used to eliminate overfitting caused in the dataset. 12% of dataset is considered for Test data . 8% of data considered for Validation and 80% is considered as train data.

Training And Testing The Model:

An Artificial Neural Network model with the following hyper parameters was used:

- Number of features as 115
- Number of classes as 3
- Size of batch as 16
- Rate of learning parameter as 0.0005

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In the proposed model Layers taken as follows

- Input --one
- Hidden --Three
- Output--One

Table1. Input output features in Each Layer

Layer Description	Number of Input Features	Number of Output Features
Input	125	512
Hidden Layer-1	512	128
Hidden Layer-2	128	64
Hidden Layer-3	64	32
Output Layer	32	3

Table1 shows Number of features taken in each layer. After each layer's result, a normalization was performed in light of its individual size and a ReLU function used function of Non linear activation.

To carry out regularization and to forbid over fitting of the model a dropout with likelihood of 0.2 is executed after each layer aside from input layer.

In the model Loss function and optimizer used were Cross Entropy and Adam optimizer Fig2 shows the confusion matrix to picture the assessment the organization. The classification report is likewise produced and is introduced underneath in figure3.

Results & Discussions

The following results were obtained after testing the model.

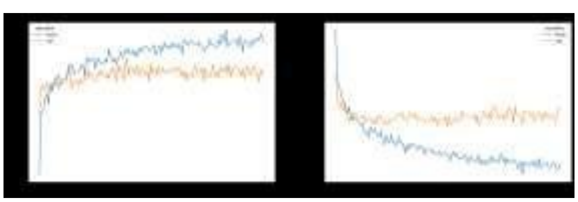

Fig 1: Track of Training and Validation Losses

```
              precision    recall  f1-score   support

           0       0.85      0.74      0.79       302
           1       0.71      0.69      0.70       302
           2       0.71      0.83      0.76       303

    accuracy                           0.75       907
   macro avg       0.75      0.75      0.75       907
weighted avg       0.75      0.75      0.75       907
```

Fig 2: Confusion Matrix

Fig 3: Classification Report

Conclusion

After training the model, it was viewed as 75% accurate in foreseeing the nature of the landslide. This work can be additionally improved by using a dataset which is balanced and then train the model with that dataset. Such datasets can improve accuracy. Different algorithms can also be implemented for different datasets to find the better algorithm which provides the best results.

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