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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR LANDSLIDES PREDICTION USING SATELLITE IMAGERY

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ABSTRACT— In hilly areas, landslides can occur due to natural factors such as heavy rainfall, earthquakes, moisture in soil, or man-made factors like unplanned constructions. Landslides can be disastrous leading to a huge loss of property and lives which can be avoided using automatic prediction. Recently, machine learning algorithms have been applied to automatically identify landslides. Numerous feature extraction and classification-based approaches have been implemented on satellite images for semiautomatic detection and prediction of landslides. However, limited research has been done on fully automatic detection with acceptable accuracy. The most challenging task in the classification and prediction of landslides from satellite images is to find an appropriate database for training and yield highly accurate testing results. The primary agenda of a comprehensive study of various techniques used for the detection and classification of landslides using satellite images is to identify the research gap. The secondary objective aims to propose a prototype of novel approach for the same task. Fifty papers based on machine learning and deep learning algorithms from reputed journals are considered for analysis. This article summarizes the performances of different classification techniques from recent literature followed by comparison and discussion with respect to accuracy. Based on the gap identified an effective prototype of the landslide classification approach is

proposed. A slightly modified version of the deep learning model ResNet101 is proposed which yields an accuracy of 96.88% when tested on an augmented Beijing dataset of 770 satellite images. The article also offers the researchers the latest status, overview, and potential avenues of machine and deep learning algorithms for landslide detection.

Index Terms – Landslide classification, satellite image classification

I. INTRODUCTION

In today's era, the utmost importance is to protect life and infrastructure from natural disasters like landslides and earthquakes. As more mountain areas are getting populated, there is an increase in national initiatives towards the safety of lively beings in the landslide susceptible areas. Landslides can cause tremendous amounts of damage to life as well as property. Landslides pose significant demographic and economic concerns in diverse countries, underlining the need for proactive risk management and international collaboration to avoid disaster-related losses. In India, 12.6% of covered land except snow-covered areas is prone to landslides. About 0.32 million sq. km area falls under the Himalayan range which is further categorized into Northeast Himalaya and North West Himalaya. Darjeeling and Sikkim fall under the North East Himalayas and cover 0.18 million sq. km area prone to landslides. North West Himalaya covers Uttarakhand, Himachal Pradesh and Jammu and Kashmir comprising 0.14 million sq. Km. Western Ghats cover Tamil Nadu, Kerala, Karnataka, Goa, and Maharashtra contributing 0.09 million sq. km and Eastern Ghat contributes 0.01 sq. km of total landslide-prone area. Himalayan range lies in earthquake Zone IV and V, these areas are susceptible to landslides initiated by earthquakes. The estimated loss of infrastructure due to landslides is 1-2 % of the gross national product in most developing countries. Estimating and minimizing the damage caused by landslides is a challenging task for the government authorities and technical teams in developing countries as approximately 80% of the casualties due to landslides are reported from these countries. Developing counties follow a steep increase in construction. Remote areas are connected to roads, railway tracks, bridges, tunnels etc. Constructions in the morphological area cause a problem in the ecosystem environment and create hazards like landslides. The danger of landslides along road alignments in North Sikkim Himalayas is evaluated by geospatial analysis utilizing thematic weighting. The results show that 65.3% of landslides occur in very high-hazard zones, which informs construction design to reduce the likelihood of future disasters. A landslide is a natural and manmade disaster that causes loss of life.

Being a developing country, construction cannot be stopped and natural parameters that trigger landslides cannot be controlled.

Therefore, an early alarm system can save lives from such hazards. Satellite image databases can be pre-processed to extract the feature to train the model for the detection of landslides with artificial intelligence. AI and machine learning are essential in the digital age for utilizing a variety of data sources and supporting spatial information analysis for catastrophe risk reduction. Recurrent and convolutional neural networks, for example, have achieved above 90% accuracy in their analyses. Landslide classification has three main stages, the first stage is the collection of images or creating datasets from satellite data.

II. LITERATURE SURVEY

A. Human vulnerability to landslides

Landslides pose a devastating threat to human health, killing thousands of people annually. Human vulnerability is a crucial element of landslide risk reduction, yet up until now, all methods for estimating the human consequences of landslides rely on subjective, expert judgment. Furthermore, these methods do not explore the underlying causes of mortality or inform strategies to reduce landslide risk. In light of these issues, we develop a data-driven tool to estimate an individual's probability of death based on landslide intensity, which can be used directly in landslide risk assessment. We find that between inundation depths of approximately 1–6 m, human behavior is the primary driver of mortality.

Landslide vulnerability is strongly correlated with the economic development of a region, but landslide losses are not stratified by gender and age to the degree of other natural hazards. We observe that relatively simple actions, such as moving to an upper floor or a prepared refuge space, increase the odds of survival by up to a factor of 12. Additionally, community-scale hazard awareness programs and training for citizen first responders offer a potent means to maximize survival rates in landslides.

B. Global patterns of loss of life from landslides

Global loss of life from landslides is poorly quantified. A global data set of fatalities from nonseismically triggered landslides that resulted in loss of life between A.D. 2004 and 2010 permits for the first time proper quantification of impacts and spatial distributions. In total, 2620 fatal landslides were recorded worldwide during the 7 yr period of the study, causing a total of 32,322 recorded fatalities. These total numbers of landslides and victims are an order of magnitude greater than other data sets have indicated, but analysis of the data suggests that it may still slightly underestimate the true human costs. The majority of human losses occur in Asia, especially along the Himalayan Arc and in China. This geographical concentration dominates the annual landslide cycle, which peaks in the Northern Hemisphere summer months. Finally, numbers of fatalities per event show a fat-tailed power law distribution, with the density of landslides being moderately correlated with the population density on a national basis.

C. Landslide hazard zones differentiated according to thematic weighting: Road alignment in North Sikkim Himalayas, India

Landslide hazard zonation mapping at regional level of a large area provides a broad trend of landslide potential zones. A macro level landslide hazard zonation for a small area may provide a better insight into the landslide hazards. The main objective of the present work was to carry out macro landslide hazard zonation mapping on 1:50,000 scale in an area where regional level zonation mapping was conducted earlier. In the previous work the regional landslide hazard zonation maps of Srinagar-Rudraprayag area of Garhwal Himalaya in the state of Uttarakhand were prepared using subjective and objective approaches.

III. PROPOSED SYSTEM

The overview of our proposed system is shown in the below figure.

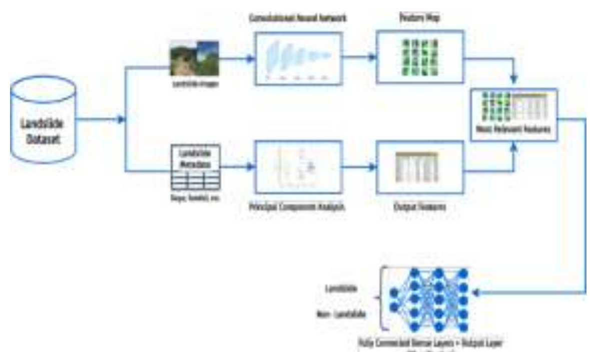

Fig. 1: System Overview

Implementation Modules

Load Dataset

- In this phase, load images .zip dataset into program and extract the images from .zip file.
- This data can be analyzed and extract the best features to preprocess the data.

Data Augmentation

- Data Augmentation is the process of increasing the size of the data set. There are ways in which the process is done by rotating, flipping, shearing, and adding random noise, along with other types. The new images in the dataset will help in training the network as well as increasing the efficiency of classifying the testing data or the new data.

Preprocessing

- In this module, we pre-process the image data and convert the image data into numpy array data. This step is very important to identify the feature of the image data. This extracted features are show as array data and size can be represented as (733, 128, 128, 3).

Train Model

- In this module, after spilt data as train and test data in the ratio of 80% and 20% respectively.

- The train data can be used for train the model and the test data can be used for test the model performance. In this project we applied CNN Model and to train the model we are using fit() method in python programming.

IV. RESULTS

Fig.2: Home Page

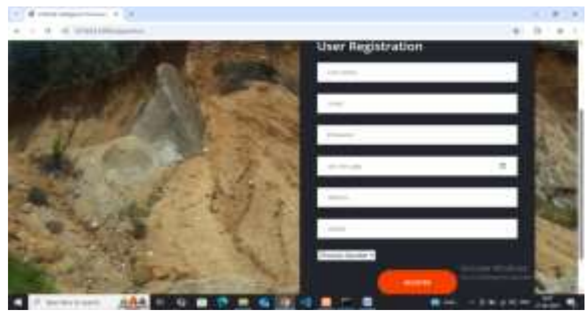

Fig.3: Registration

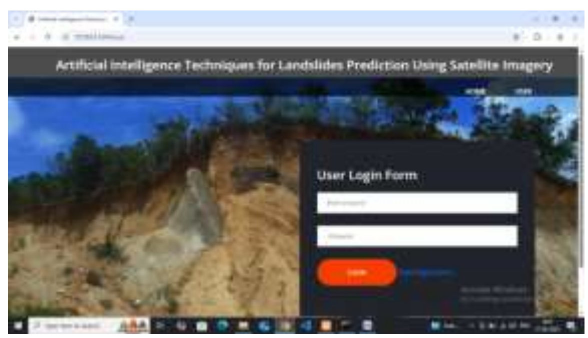

Fig.4: Login Page

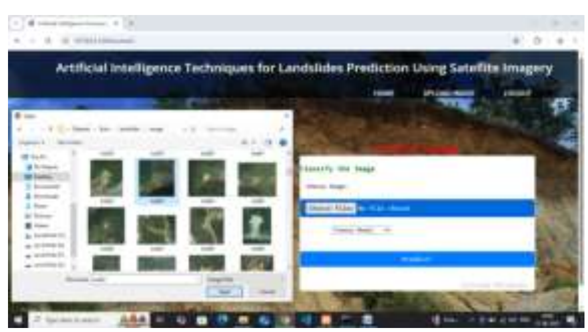

Fig.5: Upload Image

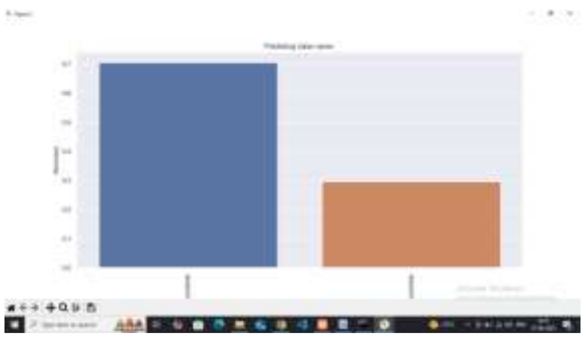

Fig.6: Predicting Result

V. CONCLUSION

This article analyses, and provides detailed comparison of different machine and deep learning techniques using various datasets of satellite images for landslide detection. Among the selected articles, 22% articles used active sensor based satellite database and 70% used passive sensor based satellite database. The accuracy in selected articles was found between 90% to 95%. This review survey reveals that a hybrid combination of different algorithms gives better classification results as compared to a single algorithm. The research gap is identified and a prototype model is proposed. The proposed model uses deep learning CNN network ResNet101 as the backbone to produce the best landslide recognition effect with an accuracy value of 96.88% and obtain the highest precision index of 96.4% with well-thought-tuned hyperparameters. Thus, the results yielded conclude that the proposed technique can provide classification of landslide data with better accuracy. Of course, there are a few limitations in this work. To alleviate the restrictions future research could combine satellite image processing with meteorological data and provide more accurate understanding of landslide detection and prediction.

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