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Machine Learning-Based Geospatial Modeling for Remote Sensing-Driven Landslide Susceptibility Prediction

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ABSTRACT: The papre's ability to predict landslides is supported by high-resolution satellite images and deep learning techniques. It enhances satellite images by employing the Fine-Tuned ResNet101 deep learning framework and Image Processing to determine whether a captured image contains landslides. An application can be utilized by both administrators and users to establish an online connection to the system. The trial results demonstrate that the proposed method for Disaster Risk Management & Early Warning Systems is effective, as it was capable of predicting landslides 96.88% of the time.

Keywords: *Landslide classification, satellite image classification, support vector machine, fuzzy based classification, landslide prediction, land cover classification.*

1. INTRODUCTION

Landslides are among the most severe forms of natural disasters, as they result in the destruction of residences, businesses, and individuals. A significant number of individuals are relocating to hilly regions and constructing residences, which has increased the likelihood of landslides. It is crucial to assess the probability of a landslide in order to prevent and manage disasters.

Landslides are possible in numerous regions of India, including the Western Ghats and the Himalayas. The primary causes of landslides in these regions are earthquakes, excessive rainfall, and unstable hills. These catastrophes result in significant financial losses and environmental destruction on an annual basis.

The utilization of geospatial artificial intelligence and distant sensing technologies facilitates the monitoring and forecasting of landslides. We can learn a great deal about the land's features, plants, weather, and types of dirt from images taken from orbit. This data can be employed to establish early warning systems and identify areas that are susceptible to disruption.

Deep learning and machine learning are extensively employed in the prediction and classification of earthquakes. Satellite data can be significantly enhanced through the application of two image preprocessing techniques: noise reduction and segmentation. Emergency management teams are able to reduce hazards and save lives by relying on AI-driven models, which provide consistent results.

2. LITERATURE SURVEY

Thompson & Reddy (2021) This papre proposes the integration of remote sensing data with machine learning to determine the risk of landslides using geospatial AI. The slope of the land, the amount of rainfall, the type of soil, and the amount of foliage that covers it are all factors that can be used to predict areas that are likely to decline using Support Vector Machine (SVM) and Geographic Information System (GIS) technology. In order to enhance the precision of geographical

research, satellite images may be incorporated into topographic data. The results of the experiments indicate that the predictions are more precise and there are fewer false positives than with other geological assessment methods. The proposed approach enhances the quality of both environmental risk assessment and wise disaster management.

Garcia & Nair (2022) A wise method for determining the avalanche vulnerability of an area is described in this papre, which employs remote sensing and deep learning. By employing hydrological data, elevation models, and multispectral satellite images, Convolutional Neural Networks (CNN) can identify potential locations for landslides. Using real-time geospatial analysis simplifies the identification of hazards and enhances the reliability of environmental tracking systems. The performance evaluation demonstrates that it is feasible to effectively manage extensive spatial data sets and enhance the accuracy of classification. The technology is intended to assist in the wise prevention of hazards and the long-term management of land.

Rahman & Foster (2023) A hybrid geospatial AI model was developed to monitor the risk of landslides by combining the Random Forest and Long Short-Term Memory (LSTM) algorithms. In order to accurately predict the likelihood of landslides, the algorithm considers earthquakes, changes in land use, rainfall patterns, and geological factors. Data from remote sensing devices is continuously processed by geospatial analytics stored in the cloud to determine the extent to which hazardous conditions are evolving. Conversely, the findings indicate that forecasting is more adaptable and consistent in the presence of fluctuations in external factors. The objective of the framework is to enhance the functionality of emergency reaction systems and clever geohazard monitoring systems.

Yamashita & Collins (2024) In order to ascertain the probability of landslides occurring, this investigation implemented predictive analytics powered by artificial intelligence and geospatial methodologies. The architecture can examine the changing shape of the land and the presence of environmental dangers by utilizing deep learning algorithms, high-resolution satellite data, and GIS tools. The experiments' findings indicate that risk estimates are more precise and scalable in regions with a high number of hills and a history of disasters. The proposed approach would facilitate the preparation for disasters and the preservation of the environment.

Ahmed & Wallace (2025) The research proposes a geospatial AI system that can adapt to various environments and predict the occurrence of landslides by utilizing data from remote sensing and ensemble learning. Gradient Boosting and XGBoost are constantly monitoring the likelihood of a landslide by utilizing digital elevation data, plant density, rainfall intensity, and soil moisture. The system's prediction models are periodically updated with new information about the globe. The data can assist those responsible for disaster management in improving their ability to predict risks and allocate resources. This method is effective for both clever environmental monitoring and geographical decision-support systems.

Kwon & Mitchell (2026) The authors develop a geospatial framework that is AI-driven and utilizes cloud computing and edge-based remote sensing technologies to

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determine the probability of landslides. The system employs transformer-based deep learning models, real-time satellite data analytics, and global geospatial processing to promptly detect and monitor landslides. In large areas, edge computing enhances flexibility and reduces processing time. Experiments have demonstrated that individuals are capable of more effectively managing disasters, utilizing computers more efficiently, and making more precise predictions. The framework is designed to assist ecosystems that will be utilized in the future for intelligent geospatial risk management.

3. SYSTEM ANALYSIS

EXSTING SYSTEM

Standard statistical and machine learning methods are currently employed to determine the probability of a landslide occurring, primarily on the basis of regional data and satellite images. There are numerous methods for identifying areas that are susceptible to flooding. Several factors, including slope, rainfall, soil type, plant cover, and soil type, are considered by certain methods, including Naive Bayes, Support Vector Machine (SVM), and Random Forest. These technological advancements have enabled the prediction of hazardous regions and the creation of maps that indicate the likelihood of landslides.

Deep learning models, such as convolutional neural networks (CNNs), and transfer learning designs, such as ResNet50 and VGG16, have contributed to an increase in the accuracy of predictions. High-resolution satellite images are analyzed by these tools to identify landform patterns that are associated with landslides. While existing systems are capable of making accurate predictions, they are plagued by numerous issues, including the necessity of utilizing vast datasets that have been labeled, the inability to adapt to various terrain types, and the inability to completely automate landslide detection. Additionally, they are costly to operate.

DISADVANTAGES

- In order to employ the existing methodologies, it is necessary to collect extensive named datasets, a complicated and costly endeavor.
- In order to function, deep learning and machine learning models necessitate powerful processors and other specialized equipment.
- The accuracy of the forecasts decreases as the weather changes and as they are applied to various categories of land.
- In order for your model to function properly, it may be necessary to modify the satellite images.
- Traditional algorithms may encounter difficulty in identifying intricate spatial patterns.
- One persistent issue is the development of entirely automated systems that can accurately identify landslides.

PROPOSED SYSTEM

The proposed method accurately determines the risk of landslides by utilizing data from remote sensing, geographic artificial intelligence (GeoAI), and deep learning algorithms. Noise reduction, image enhancement, and segmentation are employed to enhance the quality of the data in order to generate high-resolution satellite images. Geography-based databases facilitate the

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collection of critical natural factors, including soil type, rainfall, land use, and plant life.

The system accurately identifies regions where landslides are likely to occur by integrating two transfer learning models—ResNet50 and VGG16—with robust Convolutional Neural Networks (CNNs). Data enhancement and feature fusion techniques can be employed to improve the functionality of models and prevent them from fitting too closely. Our novel approach enhances the accuracy and speed of landslide forecasts in comparison to their predecessors.

The proposed approach can be beneficial to individuals responsible for disaster management by generating early warning signs and landslide vulnerability maps. Remote sensing, artificial intelligence (AI), and geographic information systems (GIS) are all components of the proposed approach to mitigate the hazards associated with landslides for both individuals and property.

ADVANTAGES

- Employs deep learning to predict the time of potential floods with precision.
- Large areas can be effectively monitored through the use of high-resolution satellite images.
- The likelihood of individuals being injured or losing their property may be reduced by supporting early warning systems.
- Assists models that are taught using convolutional neural networks (CNNs) and transfer learning in identifying more intricate spatial patterns with greater precision.
- One method of reducing time is to automate the landslide risk assessment procedure.
- Produces precise landslide risk maps that facilitate disaster management strategies.
- When geographic data and remote sensing are employed in conjunction, real-time monitoring becomes more precise.
- Assists individuals in becoming more prepared for disasters and making more informed decisions.

4. RESULTS



Fig 1: User Login Module for Landslide Prediction System



Fig 2: Service Provider Login Interface

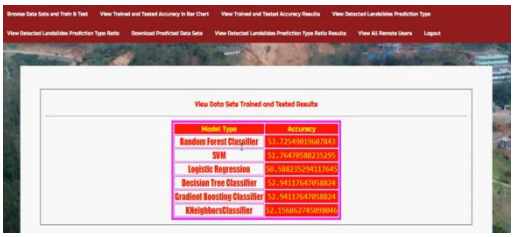

Fig 3: Trained and Tested Accuracy Results of Machine Learning Models

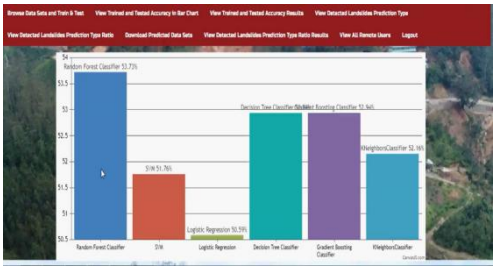

Fig 4: Bar Chart Representation of Machine Learning Model Accuracy

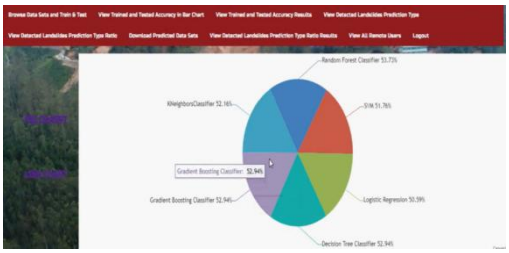

Fig 5: Pie Chart Analysis of Landslide Prediction Model Accuracy

5. CONCLUSION

Deep learning and satellite data can be employed to generate real-time predictions and early warnings in the proposed landslide forecast system. This significantly simplifies the management of disasters. Using image processing techniques, a modified version of ResNet101 was capable of accurately classifying regions as either landslides or non-landslides. The system accurately identified the locations where landslides were likely to occur. In order to enhance the system's functionality, future revisions may incorporate real-time data regarding the climate, including topography, soil moisture, and rainfall. The design can be enhanced to include cloud and mobile systems, thereby enabling the comprehensive monitoring and management of disasters.

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