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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR LANDSLIDES PREDICTION USING SATELLITE IMAGERY

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ABSTRACT

Heavy rain, earthquakes, and soil wetness are some of the natural causes of landslides in mountainous regions. Human actions, such as haphazard building, may also contribute to this problem. Effective forecast systems might lessen the impact of these catastrophes, which can cause severe property damage and loss of life. Recently, ml algorithms have been used for autonomous landslip detection and prediction. The semi-automatic identification of landslides has made use of satellite data and a variety of feature extraction and classification methods. Still, there's a ways to go before completely automated detection can compete with human precision. One of the biggest challenges is finding a trustworthy training database that produces accurate testing results. In order to find where the current research is lacking, this study reviews all the methods that have been employed to date for landslip categorisation and detection using satellite imagery. It also suggests a new model for landslip forecasting. The accuracy and categorisation methods used in these articles are examined, providing a window into the present and potential future. To further develop the application of ml, especially CNN models, for landslip detection from satellite images, the suggested prototype employs dl models to enhance landslip detection and classification.

I.INTRODUCTION

Areas characterised by steep topography, excessive rainfall, or human-induced disturbances like deforestation and urbanisation are more likely to have landslides, which are natural catastrophes that may result in substantial casualties, property damage, and community disruption. Geological surveys, ground-based measurements, and historical data are the mainstays of traditional landslip prediction techniques. However, these approaches may be costly, time-consuming, and inadequate for locations that are difficult to reach. A potential approach for better landslip prediction and risk assessment has been the integration of AI with satellite imaging in recent years. The use of high-resolution sensors on board satellites allows for the provision of precise, up-to-the-minute information on landslip risk variables such as topography, vegetation, and precipitation. In order to analyse this massive and complicated satellite data for trends and to forecast landslide-prone locations, artificial intelligence methods like ML and DL are used.

Predictive models that aid in the identification of high-risk zones may be generated by AI-driven systems that automatically analyse and analyse satellite images, taking into account a variety of characteristics like terrain, soil moisture, land cover, and rainfall patterns. To better plan for and respond to possible landslip disasters, these models may be used to develop early warning systems, hazard maps, and tools for real-time monitoring.

This method not only makes landslip prediction more precise and efficient, but it also offers a scalable, cost-effective way to keep tabs on huge areas, even in places that aren't often watched. Early warnings and educated decision-making for disaster management and urban planning might be greatly enhanced by combining AI with satellite technology to reduce the effects of landslides and save lives.

To better evaluate landslip risk and manage disasters, this study delves into the artificial intelligence (AI) methods used for landslip prediction using satellite images, discussing their uses, difficulties, and potential future directions.

To enhance landslip prediction and risk management, the suggested approach integrates satellite images with contemporary AI methods like ml and dl. Topography, vegetation, soil moisture, and rainfall patterns are among the important aspects that the system retrieves by analysing high-resolution satellite data. In order to provide authorities and communities early warning warnings about locations that might be prone to landslides, AI models examine these properties in real-time. Urban planners and first responders may use the system's dynamic danger maps as a tool. Overcoming the constraints of existing ground-based approaches, this technology provides scalable, cost-effective, and accurate monitoring.

II.METHODOLOGY

A) System Architecture

In order to forecast the likelihood of landslides in different areas, the system architecture for Landslide Prediction using Artificial Intelligence (AI) methods in conjunction with satellite images is planned to effectively handle and analyse massive amounts of remote sensing data.

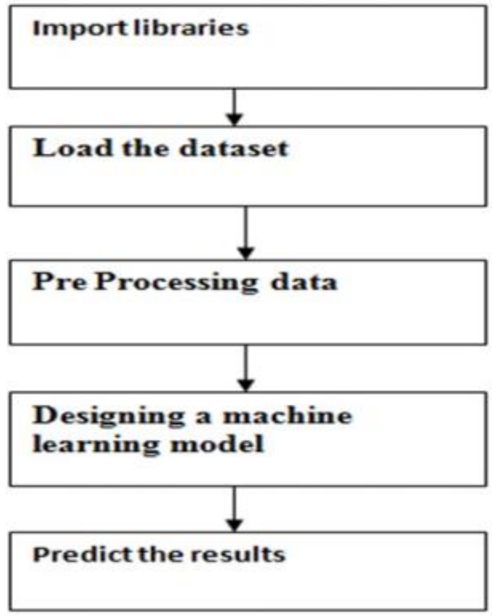

Fig1.System Architecture

In order to forecast the likelihood of landslides in different areas, the system architecture for Landslide Prediction using Artificial Intelligence (AI) methods in conjunction with satellite images is planned to effectively handle and analyse massive amounts of remote sensing data. The system's several linked layers ensure that the AI model can provide accurate and real-time predictions by handling data collecting, preprocessing, model training, and deployment. The data collection layer is crucial to the design and gathers geographical data and satellite images from many sources such as Google Earth Engine, NASA, and other remote sensing platforms. Data including topography, elevation, land use, soil moisture, rainfall levels, and plant covering are often included in these satellite photos, which are taken at regular intervals. Heavy rainfall, seismic activity, or quick temperature fluctuations are all examples of real-time weather patterns that the algorithm takes into account when predicting the likelihood of landslides. The data preparation layer becomes active when data collection is complete. In this stage, the raw geospatial data and satellite images are cleaned and prepared for analysis. To make sure the satellite pictures are clear enough for feature extraction, image preprocessing methods are used, such as noise reduction, image enhancement, and cloud removal. In order to make geospatial data usable across several models, it is normalised and aligned with suitable geographic coordinates. In addition, characteristics that may identify regions prone to landslides, such as changes in land cover, slope steepness, and picture segmentation, are extracted from the satellite data using methods including texture analysis, edge recognition, and image segmentation.At its heart is the architecture's machine learning and AI layer, which trains many prediction models using satellite images and data on past landslides. Specifically designed for picture classification problems, supervised learning methods like convolutional neural networks (CNNs) are used by these algorithms to identify characteristics and patterns linked to previous landslides. Furthermore, landslip risk may be predicted using extracted data such rainfall intensity, soil moisture, and slope characteristics using Random Forests or SVM. The artificial intelligence algorithms learn to detect possible landslides by analysing labelled datasets that include locations with a history of landslides.

B) Proposed Deep Learning-Based Model

The outlined To effectively analyse complex, high-dimensional information and anticipate possible landslip hazards, a model is developed that uses deep learning to analyse satellite images and environmental data. In order to aid in the real-time forecasting of landslides, this model makes use of machine learning algorithms to analyse and comprehend satellite imagery in conjunction with other environmental elements. After that, important characteristics may be derived from the satellite images using the feature extraction procedure. Images may be effectively annotated with features using Ml models, and CNNs in particular, to reveal things like slope gradients, soil erosion patterns, and plant stress, which might point to places prone to landslides. Features like topographical height, land-use categorisation, and soil composition are also extracted by geospatial analysis. A feature vector is generated from these characteristics and other environmental data, such as rainfall and temperature, and then fed into the machine learning model. Convolutional Neural Networks (CNNs) are great at detecting patterns and spatial hierarchies in images, making them ideal for the satellite image processing aspect. By analysing the photos, these CNN algorithms can determine which pixels or locations are most likely to have landslides. Cracks, soil disturbance, or changes in flora health are visual signals that the CNN may be taught to recognise. These characteristics can predict the approaching occurrence of a landslip. By automatically learning high-level information from the satellite photos, deep learning models may further increase forecast accuracy without operator involvement. Next, a testing dataset is used to evaluate the model. This dataset includes data from locations that were not included during training.These measures are useful for evaluating the model's true positive rate, false positive rate, and propensity to overlook crucial regions when identifying landslide-prone locations. To further strengthen the model and avoid overfitting, cross-validation methods like k-fold cross-validation may be used. The model may be used in real-world applications if it reaches an acceptable level of accuracy and generalisability. Users may upload fresh environmental data and satellite photos into the prediction layer to receive landslip risk forecasts. A risk map may show these projections as coloured areas with different levels of expected landslip danger. In order to help disaster management authorities make decisions, the system may output risk ratings as low, medium, or high.

C. CNN Based Landcover Classification Techniques

Convolutional neural networks (CNNs) are now the gold standard for landcover categorisation, particularly when using satellite images. One subset of deep learning algorithms, convolutional neural networks (CNNs) are very good at extracting patterns and hierarchies from visual data. The CNN is often fed a satellite picture with data from many bands (e.g., red, green, blue, near-infrared, etc.) in each pixel, which is called a multi-spectral or multi-temporal image. To feed information into the network, we use the pixel values. The nucleus of the convolutional neural network (CNN) is the layer that actually performs the convolution. In order to extract local characteristics like edges, textures, and patterns from an input picture, convolution slides a tiny filter over it. For each particular picture, the mathematical expression of the convolution procedure is:

$$(I * K)(x, y) = \sum_{m} \sum_{n} I(x + m, y + n) \cdot K(m, n)$$

The activation function, usually ReLU, is applied to the output after every convolutional process. By making the network non-linear, the ReLU function enables it to learn intricate patterns. We define the function as:

$$\mathrm{ReLU}(x) = \max(0, x)$$

By deleting negative values, this function allows the network to learn successfully. It does this by outputting the maximum of the input value and zero.

In order to simplify computation and save just the most important information, the pooling layer decreases the spatial dimensions of the feature maps. By far the most used pooling operation is max pooling, which involves choosing the highest value in a sub-region:

$$\text{Max Pooling}(x, y) = \max(I(x, y))$$

The last step involves passing the output through a series of fully connected layers after it has been flattened into a 1D vector by means of several convolutional and pooling layers. The final categorisation results are produced by these layers. For multi-class classification, the last layer usually calculates the probability of each class using a softmax function:

$$P(y_i|x) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

To train a convolutional neural network (CNN), one must minimise classification error by modifying the weights of the fully connected layers and convolutional filters. The backpropagation algorithm in conjunction with an optimisation technique, such as Stochastic Gradient Descent (SGD) or Adam, is usually used for this purpose. The goal is to find the loss function with the minimum value, which may be categorical cross-entropy:

$$L = -\sum_{i=1}^{C} y_i \log(p_i)$$

Combining CNN-based landcover classification with satellite data may greatly enhance landslip prediction. Important landcover types may be identified by the model, including forested regions, urban centres, and landslip-prone slopes. The system's ability to categorise landcover into various groups will aid in the detection of landslide-prone areas, which will enable earlier warnings and more effective disaster management.

D. Feature Selection

Building a machine learning model to forecast landslides using satellite images relies heavily on feature selection. Improving model performance, reducing computing complexity, and preventing overfitting are all goals of feature selection from large sets of input data. The dataset for landslip prediction includes several variables, such as topographical features, environmental variables (such as temperature and seismic activity), and features from satellite images (such as elevation, slope, land cover, soil moisture, rainfall data, and more). To help the ml model zero in on the most important aspects, feature selection seeks to determine which of these variables has the strongest correlation with landslip occurrences. As an example, landslip risk may be effectively predicted by considering factors such as slope steepness, soil wetness, and rainfall intensity. Consequently, these characteristics have to be kept, whereas elements that are less important or unnecessary (such regional temperatures, for example) may be eliminated.When working with satellite images, there are a number of methods for selecting features. One popular approach is correlation analysis, which involves identifying characteristics with strong correlations and removing variables that are redundant. To avoid overfitting, this checks that the model isn't putting too much weight on any one input variable. Mutual information is another well-liked technique; it evaluates the connection between the goal variable and each characteristic.(event of a landslip). We keep the features that tell us the most about the target and get rid of the ones that don't.Furthermore, feature selection may make use of tree-based techniques like RF and GBM, which naturally prioritise features while training the model. We may simplify the model without compromising accuracy by removing features with lower significance ratings. Another effective method is Recursive Feature deletion (RFE), which involves systematically reducing the feature set by repeatedly removing features and evaluating the model's performance after each deletion.

These feature selection strategies allow the model to zero in on the most important variables, which improves training efficiency and generalisability to fresh data. Stakeholders may get a better understanding of the elements driving landslip risk via improved prediction accuracy and interpretability brought about by appropriate feature selection.

III.CONCLUSION

The use of artificial intelligence methods to forecast landslides using satellite images has shown promising results. Improved landslip prediction and early warning capabilities, enabled by the integration of satellite data with state-of-the-art ml and dl models, may save lives and reduce property damage. Nevertheless, there is always room for development and more study in areas like data quality, generalising models, and integrating different data sources.

IV.REFERENCES

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