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A SURVEY ON AUTOMATIC LANDSLIDE DETECTION USING SATELLITE IMAGES

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Abstract

Detection of landslides is an important part of disaster management, as it permits the government to act swiftly to reduce the damage resulting from landslides. The possibility for landslide detection to save lives, maintain ecological balance, and optimize the use of limited resources and physical infrastructure is enormous. If government officials are able to spot landslides early on, they can take steps to lessen their impacts. Manual monitoring is commonly used in traditional landslide detection techniques, but this takes time and a lot of manpower. In contrast, AI-based landslide detection has significant benefits over conventional techniques. Because AI algorithms are capable of processing vast amounts of data in real-time, they can be used to detect and respond to landslides much more quickly. This literature review looks at how AI can be used to analyse satellite images for detecting landslides. Landslide-prone locations can be identified with the help of AI, which can scan massive volumes of satellite imagery data, segment the data, and extract the features that are important. Several artificial intelligence (AI) methods, such as Machine Learning (ML) and Deep Learning (DL) algorithms, are discussed in this paper. Several challenges associated with putting an AI model to work on satellite images are also covered. In conclusion, this study is going to be of interest to scholars and practitioners in the fields of disaster management and geospatial analysis since it gives helpful insights into the implementation of AI algorithms for landslide identification.

Keywords— Landslide, Satellites, Remote Sensing, Machine Learning, Images, Radiometric, Neural Network, Class Imbalance.

I. INTRODUCTION

A landslide is simply the downward movement of rock, rubble, or earth caused by gravity. It is a catastrophic natural phenomenon in hilly areas of the Indian continent and other parts of the world. When this occurs, the consequences for buildings, houses, and people can be severe. Landslides are dangerous natural hazards in hilly areas, therefore identifying them early and estimating the damage they cause to property and infrastructure has been an intriguing problem.

Geological hazards (debris flows and landslides) have risen in frequency and intensity in recent years as a result of climate change, earthquakes, and rising urbanization [1]. Landslides are a widespread danger in sloped terrestrial landscapes in metropolitan areas, along traffic corridors, and at rural industrial sites [2,3]. From January 2004 to December 2016, 4862 different landslides claimed the lives of 55,997 individuals, as recorded by the Global Fatal Landslide Database (GFLD).

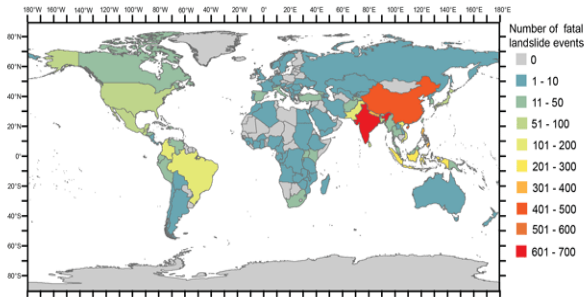

Figure 1. Landslides across the globe (2004 to 2016) [4].

Figure 1 depicts the uneven distribution of landslides, with Asia accounting for 75% of all landslides. Mountains, cliffs, and even the ocean floor can all experience landslides due to their varying degrees of steepness or gentleness. Landslides typically result from geological factors such as weathered rock, fissured, sheared, or bonded rock substance, contrasted soil elements, and poor rock adhesiveness [5]. Landslides are also caused by deposition and weathering, as well as other types of erosion down a slope, such as water, fluvial, wave, and glacier erosion [6]. Gravity is the main force behind a landslide. Many landslides occur as a result of external forces such as rain or earthquakes, or as a result of human operations that expose the ground, such as excavating a slope for a road.

A. Importance of landslide detection

This area of study has altered its focus to answer this important need, as landslides cause deaths and injuries on roadways in many regions of the world every year. Urban planners and risk managers can benefit greatly from more advanced landslide detection technology. The second most lethal natural disaster after earthquakes and tsunami is landslides. Most landslide area (66.5%) is located in the Indian subcontinents, specifically in the Northwest Himalayas (Himachal Pradesh, Ladakh, Jammu & Kashmir, and Uttarakhand) [7]. Urban planning must take into account the detection of both active and inactive landslide locations, as well as the identification of risk-prone zones. Due to the importance of researching the level of activity and spatial distribution of landslide processes, landslide detection is a crucial step in improving land management, urban design, and then safe occupation in mountainous regions for such natural dangers.

Accurate forecasts and warnings are necessary to prevent material and human losses. When preparing for and responding to natural disasters, knowing what triggers landslides and how to mitigate their effects is crucial. Size, form, and surface morphological changes make identifying landslides a difficult and complex task. The topic of how to rapidly and reliably identify landslides and anticipate their occurrence remains unanswered, despite the fact that various approaches have been offered. Using satellite images in conjunction with Geographic Information Systems (GIS) and on-the-ground investigations, the geomorphological circumstances under which historical disasters occurred can be correlated to expected future ones [8]. Remote sensing is widely employed for collecting features along with exposing landscape modifications, the factors causing the landslide, and the procedure of recovery. Because of this, exciting new possibilities for early prediction, identification, and assessment of tectonic or climatic natural hazards with potential economic, social, and environmental repercussions have opened up thanks to advancements in information processing technologies and AI. This survey looks at ways to identify landslides in satellite images using AI techniques.

II. Process Flow

The conventional method for detecting and mapping landslides is field investigations, which are part of the geomorphological analysis. Old landslides are challenging to spot with this strategy. AI-based autonomous landslip detection is crucial for preventing this. As a whole, the experimental procedure has six stages. First, samples of landslide images were prepared from the satellites. Second, the obtained images underwent preliminary processing to strip out the irrelevant information. Third, segmentation is performed after the images have been processed, and there are four different segmentation techniques are available. Fourth, methods such as spectral analysis, textural analysis, shape analysis, and topographical analysis are used to obtain the crucial features from the segmented images. Fifth, AI models based on ML or DL were employed to identify landslides. Finally, the effectiveness of the landslide detection model was assessed. In Figure 2, we can see the full experimental setup used for automatic landslip detection.

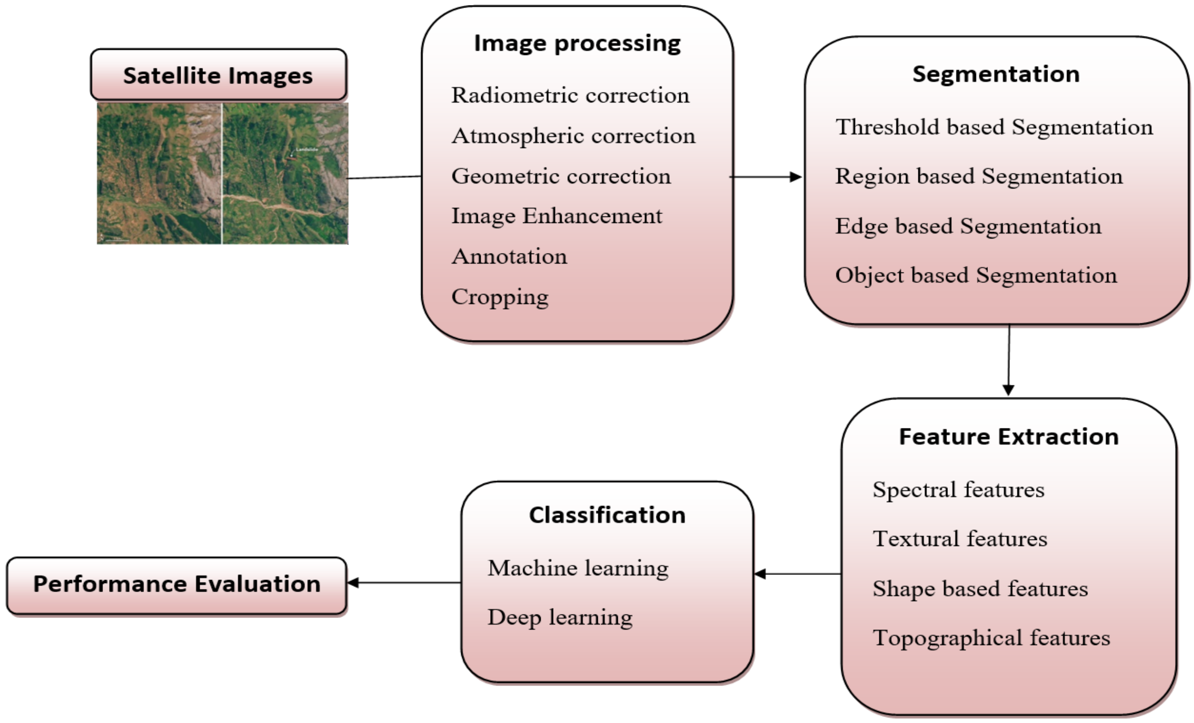

Fig. 2. Flow of Landslide Detection using AI

III. Data Acquisition

Landslides can be detected from satellite images using a variety of publicly available databases. Some of the datasets are detailed below

The Bijie landslide dataset [9] contains 770 landslide samples and 2003 non-landslide samples for the city of Bijie in Guizhou Province. Images of rock slides and falls predominate in the landslide collection, whereas images of mountains, towns, roads, rivers, woods, and crops can be found in the curated environmental remote sensing collection. We believe this dataset to be the first of its kind available to the public; it is both high-quality and extensive, and it was gathered via remote sensing. Landslides were manufactured to encourage investigation into automatic landslide recognition via optical remote sensing images, despite regional differences in landslide characteristics.

The LongRange Sichuan-Tibetan Corridor (LRSTTC) dataset [10] was built with the help of human visual assessment of Google Earth images of the corridor. (1) Since landslides typically occur in regions with noticeable spatial and temporal changes in optical images, new landslides can be easily spotted using Google Earth images. (2) Many geomorphological features can be used to identify previous landslides. In addition to expert verification, some landslides in the LRSTTC dataset were checked in the field.

FORMOSAT-2 [11], which provides high-resolution, inexpensive imagery, is still owned by Taiwan. FORMOSAT-2 imagery is superior to previous satellite images for monitoring landslides in Taiwan over time. As an optical satellite, FORMOSAT-2 uses four multispectral bands. Panchromatic bands have a resolution of 2 meters, while multispectral bands resolve at 8 meters. The imagery has an 8-bit radiometric resolution. A land cover map is included with every piece of imagery. On a land cover map, you can find the "ground truth" labels for the data. Each pixel in the image is given its accurate classification. Using manually processed images, land use is mapped. Vegetation, water, riverbed, landslides, and other land uses (including farms and settlements) are the five types of land cover in this model.

In the Landslide4Sense [12] (L4S) benchmark data collection, Sentinel-2 multi-spectral (band1-band12), DEM, and ALOS PALSAR slope data make up 13 of the 14 data layers. Multi-spectral Sentinel-2 (band1-band12) data, a DEM, and slope data from ALOS PALSAR are only some of the 14 layers that make up the L4S competition's benchmark data set. The L4S dataset contains 3,799 image patches for training, 245 for validation, and 800 for testing.

Landsat-8 data [13] has both optical and infrared (OLI) and thermal (TIRS) detectors. With a spatial resolution of 30 m for eight of the nine shortwave spectral bands and just 15 m for the panchromatic band, the OLI gathers imagery over an area of 185 km 30 km. Over an area of 185 kilometres, the TIRS captures thermal imagery with a resolution of 100 meters in two thermal bands.

Sentinel-1 and Sentinel-2 data [14] are collected from Earth-monitoring satellites launched by the European Space Agency (ESA). High-resolution remote sensing imagery from both satellites is crucial for locating, mapping, and keeping an eye on landslides. High-resolution radar images of Earth's surface are acquired by the Sentinel-1 synthetic aperture radar (SAR) satellite around the clock, every day of the week. SAR data is excellent for spotting landslides even in locations with regular cloud cover or extensive vegetation because it can see through both. Sentinel-1 radar images can be used to spot landslides by inspecting them for signs of abnormal ground elevation or displacement, as well as for changes in surface roughness and scattering quality. The optical multispectral imaging satellite Sentinel-2 captures images of Earth's surface in a high resolution across 13 spectral bands. Using Sentinel-2's high spatial and spectral resolution images, landslides and other types of land cover can be precisely detected and mapped. Sentinel-1 and Sentinel-2 time series images can also be used to monitor the development of landslides and evaluate the risks they pose over time.

ALOS World 3 D-30m (AW3D30) [15] is chosen as the Digital Elevation Model (DEM) input due to its global spatial coverage (600 S to 600 N latitudes), availability, and time span coverage (2006 to 2011). The dataset also includes a Digital Surface Model with a resolution and a horizontal GSD of 5m and 30m. The DEM is employed in determining the gradient of a landscape. This is based on the four neighboring pixels (Bottom, top, left, and right of the central pixel) in the image.

IV. Image Processing

Improving an image or extracting useful data from it are both examples of image processing. Several distortions have to be fixed before the data can be evaluated and post-processed. Pre-analysis image processing includes any steps taken to eliminate or reduce artefacts brought on by the camera, sensor, or observing conditions. Common examples of pre-processing work include:

A. Radiometric Correction

Radiometric aberrations are caused primarily by sensor properties and illumination conditions. When the time a picture was acquired does not match the time energy from the objects in the image was emitted or reflected, common imaging difficulties develop. Before any useful analysis or interpretation of the photos can be undertaken, the radiometric distortion must be addressed. The two basic types of radiometric corrections are Sensor Irregularities and Sun Angle/Topography Radiometric Corrections. The Sun radiometric corrections limit the impacts of diffuse sunlight by forecasting the shade curve, notably at the water's surface and in the mountains [16]. Radiometric noise generated by fluctuations in sensor sensitivity or sensor degradation, on the other hand, is reduced via sensor irregularity adjustments [17]. As part of the correction procedure, a new set of correlations between the calibrated irradiance measurement and the sensor output signal is computed. This method is also known as calibration.

Landsat Collection 1 data, for example, is available in both tiers 1 and 2, is radiometrically adjusted, and varies in quality. Tier 2 scenes are radiometrically compatible with Tier 1 scenes, but they do not meet the Tier 1 geometry standards due to factors such as severe cloud cover, insufficient ground control, or less precise orbital information from an earlier Landsat sensor.

B. Atmospheric Corrections

Radiation from the Earth's surface interacts with the atmosphere several times before reaching the sensor. Clouds and pollution in the atmosphere, for example, can make it difficult to observe clearly. As a result, ambient noise appears in many photos and must be eliminated for proper representation [18]. The two basic types of atmospheric correction approaches are the Absolute Correction Method (ACM) and the Relative Correction Method (RCM). The ACM corrects for atmospheric distortions by taking into consideration a number of time-dependent characteristics such as solar zenith angle, sensor observing angle, aerosol cumulative optical depth, and upper-atmosphere irradiance. However, precise measurements of the atmosphere are difficult to obtain, and absolute correction methods are notoriously complicated. We typically use RCM, which entails aligning a series of photos captured on different dates inside the same scene to an external reference image.

C. Geometric Correction

Geometric distortions in remotely sensed data are widespread as a result of factors such as altitude, sensor, or earth oscillations. In an ideal scenario, we'd have two photographs taken at different times of the same area on the ground, each identified to the exact pixel. We need to make geometric adjustments to account for these geometric distortions and determine the link between the image CRS and the Geographic CRS if we want greater spatial coincidences between the images [19]. Image-to-map rectification or image-to-image registration (co-registration) is used to make geometric modifications by establishing affine linkages with ground control points in both the image CRS and the Geographic CRS. The manual identification time and effort required by traditional geometric fixes [20] are significant disadvantages. Orthorectification requires more data than georeferencing with ground control points, however, providers are increasingly offering this service as a result of advances in remote sensing technology. Most earth observation applications necessitate orthorectification to correct inaccuracies induced by sensor tilt and terrain (relief displacement).

Both the Landsat 8 OLI data and the Sentinel-2A MSI outputs contain geometrically adjusted images.

D. Image Enhancement

The satellite photographs are dark and foreboding. As a result, it's critical to improve photos while retaining vital details. When analyzing an image's quality on a more subjective level, contrast is an important component to consider. To discern these distinctions, human vision relies on the contrast between objects and their backgrounds. It is the hue and intensity contrast between the foreground and backdrop.

Numerous techniques have been developed to improve contrast and address other brightness-related issues in image processing. Image enhancement methods are classified into two types: spatial and frequency domain [21]. This technique is required while preparing datasets to improve image quality. We need higher-quality remote-sensing photos for effective training if we want to employ DL algorithms for image categorization. Low-illumination optical remote sensing images fail to deliver when it comes to image classification and recognition due to their dismal aesthetic impacts and modest feature deviations [22].

E. Annotation

Landslide borders are recognized in remote sensing photos using supervised semantic segmentation. Semantic segmentation assesses whether or not an area portrayed in an image is part of a landslide pixel by pixel. Ground-truth labels are required to train and assess supervised semantic segmentation models [23]. Model evaluations are tainted by noise caused by labeling errors. As a result, it is critical to draw exact borders around landslide sites.

Existing landslide mapping findings for the newly obtained picture are incorrect due to differences in vegetation cover and the shapefile. We took aerial remote-sensing images of landslides and manually mapped each one. The shapefile comprised the landslide boundaries that were discovered throughout the mapping process.

F. Cropping

DL-based landslide detection techniques require a lot of GPU memory and processing power. The initial remote sensing image is too large for landslide detection with CNNs or Transformers. It must be divided into manageable sections. Remote sensing photos with higher resolution show more complex information on landslides than ever before. Meanwhile, an image patch of uniform size represents a small region of the world. A big patch size causes GPU memory overflow in this circumstance, whereas a small patch size cannot cover wide-scale landslides. It is critical to find a balance between these factors [24].

V. SEGMENTATION

The process of dividing an image into different sections or segments based on parameters such as luminance, color, texture, and shape is known as segmentation. Segmentation is an important stage in landslide identification from satellite pictures because it allows for the localization and mapping of landslide areas [25]. Landslide detection can make use of a variety of segmentation techniques, such as threshold, edge, region, and object-based approaches.

A. Threshold-based segmentation:

These threshold-based image segments are straightforward and commonly used. The threshold value in landslide detection can be changed based on the spectral qualities of the landslide [26], such as its brightness, color, or texture. The threshold value can be determined by hand or automatically using statistical procedures such as Otsu's method [27]. This technique may be effective for finding landslides that have a substantial spectral difference from their surroundings.

B. Region-based segmentation:

An image is separated into portions using this method based on the degree of pixel similarity between them. The similarity can be characterized using textural, spectral, and contextual elements of the image [28,29]. Watershed segmentation and mean shift clustering are two region-based segmentation algorithms used in landslide detection. This technique can be useful for locating landslide hotspots with modest color and texture changes.

C. Edge-based segmentation:

This technique can employ edges or other dramatic changes in an image to produce discrete portions. To determine the borders of land cover classes or objects, satellite images can be processed using edge detection techniques including Sobel and canny edge detectors [30]. Landslides with well-defined boundaries are great candidates for detection using edge-based segmentation.

D. Object-based segmentation:

This technique segments an image based on the recognition and separation of items or features within the image. Image attributes such as shape, size, and texture are retrieved and used to cluster related pixels into larger objects in order to perform object-based segmentation [31]. Using object-based segmentation, regions prone to landslides can be recognized by separating the satellite image into its component land cover categories.

VI. Feature Extraction

A technique called feature extraction is employed to discover and extract relevant data from segmented satellite images for landslide identification [32]. Satellite images can be studied for features that help distinguish between different types of land cover or locate areas in danger of landslides. Some of the feature extraction techniques that can be used for landslide detection include spectral features, texture features, and form features.

A. Spectral features:

The spectrum properties of an image, or how it reflects or emits electromagnetic radiation at different wavelengths, form the basis for spectral features. To extract spectral features, different bands of the satellite image, such as the near-infrared, visible, and thermal bands, can be employed. Spectral features include the mean, minimum, maximum, standard deviation, and variation of pixel values. These features can be used to classify different types of land cover, as well as to locate places prone to landslides.

B. Textural features:

We refer to the spatial distribution of the image's pixel values as its "textural features." These features can be extracted using statistical measures such as co-occurrence, gray-level run-length, and difference matrices. Textural features include contrast, homogeneity, entropy, and correlation [33]. Textural patterns may indicate areas that are more prone to landslides, and these areas can be identified using texture features.

C. Shape-based features:

Shape-based features define the geometric aspects of the items in an image. These features can be built using information on the position, size, and orientation of objects in an image. Shape-based features include circularity, area, compactness, perimeter, and length. Shape-based features can be used to identify landslides with distinctive geometric characteristics, such as elongated or irregular shapes.

D. Topographical features:

Topographical features such as slope, aspect, curvature, and elevation can all be inferred using DEM [34]. Geographic variables affect slope instability [35,36].

Certain topographical features, depending on the terrain, can be used to pinpoint locations prone to landslides.

E. *Spectral features:*

Spectral features are based on the spectral characteristics of the image, which refers to the way in which the image reflects or emits electromagnetic radiation at different wavelengths. Spectral features can be derived from different bands of the satellite image, such as visible, near-infrared, and thermal bands. Spectral features include mean, standard deviation, maximum, minimum, and variance of the pixel values. These features were utilized to differentiate between different land cover types and identify areas of potential landslide activity.

VII. CLASSIFICATION

Landslide classification using satellite images can be done using various techniques like ML and DL [37-40].

A. *Machine Learning*

Because ML techniques can automatically learn and identify complex patterns and features in data, they are increasingly being used to detect landslides using satellite images. The following are some popular ML algorithms for spotting landslides in satellite images:

1. MLC (Maximum Likelihood Classifier): Because the spectral signature is assumed to have a normal distribution, this method is a statistical classifier. It estimates the possibility that a pixel belongs to each class based on its spectral values and places it in the class with the highest probability.
2. SVM (Support Vector Machine): SVM finds the optimal hyperplane for class separation in high-dimensional feature spaces. SVM first transforms the input into a higher-dimensional space before classifying it. The hyperplane that divides the groups effectively is then identified.
3. DT (Decision Tree): DT is a simple and effective algorithm that operates by segmenting the feature space into decision rule hierarchies. It separates the data into subgroups depending on the feature with the most informational value until a stopping requirement is satisfied.
4. RF (Random Forest): The RF method is an ensemble learning strategy that uses a combination of several DTs to improve classification precision. RF trains multiple decision trees on distinct sections of the training data and then combines the results to create correct predictions.
5. NN (Neural Networks): The term "NN" refers to a class of ML algorithms that draw inspiration from how the human brain functions. They learn a set of weights in order to provide correct class labels from input information. NN may be used for pixel-based classification of satellite photographs by training the network using labelled data and then applying it to new images.
6. K-means clustering: K-means is a simple and effective clustering approach that splits data into K groups based on common criteria. The approach starts by randomly allocating K centroids and then refines those centroids until convergence is attained.
7. Hierarchical clustering: Hierarchical clustering is one technique for breaking down clustering algorithms into progressively granular stages. The algorithm first treats each data point as a separate cluster before combining them in later rounds based on similarities.
8. SOM (Self-Organizing Maps): SOM, a neural network-based clustering approach, can execute its clustering magic by projecting the input data onto a low-dimensional grid of nodes. The grid's nodes indicate clusters and data points are assigned to the one that is geographically closest to them.
9. PCA (Principal Component Analysis): PCA is a dimensionality reduction technique used to minimize data

variance and then group it with K-means or hierarchical clustering.

10. (FCM) Fuzzy c-means clustering: In the FCM soft clustering procedure, each data point is assigned a membership weight for each cluster. The membership weights indicate how well a data point fits into a cluster. The algorithm iteratively updates the membership weights and cluster centres until convergence is obtained.

B. *Deep Learning*

The purpose of DL, a branch of ML, is to train neural networks with multiple layers to automatically learn and detect complex patterns and characteristics in data. The ability of DL techniques to handle massive and high-dimensional data and identify minor landslide properties has resulted in promising outcomes in the context of landslide recognition in satellite images. Some prominent DL approaches for detecting landslides in imagery from satellites are as follows:

1. CNNs (Convolutional Neural Networks): CNNs are a well-known DL approach for image classification. They do this by extracting spatial properties at various scales from the input image using convolutional filters. These features are transmitted through a network of completely linked layers to generate a classification result.

2. RNNs (Recurrent Neural Networks): RNNs, a form of DL algorithm commonly used for sequential data analysis, can help with satellite picture time series. They work by taking in data one piece at a time and processing it while keeping a secret record of it. The hidden state must be updated at each time step for the network to recognize temporal dependencies and patterns.

3. CRNNs (Convolutional Recurrent Neural Networks): Convolutional neural networks (CRNNs) are used to classify images and videos. They work by first passing the input image through convolutional filters to extract spatial properties, followed by recurrent layers to capture temporal correlations and patterns.

4. DBNs (Deep Belief Networks): DBNs are a DL technique for unsupervised feature learning and categorization. Unsupervised learning is used to learn a hierarchy of representations from the incoming data. Each succeeding layer in the hierarchy learns a compressed representation of the input, which can then be utilized for classification.

5. DCNNs (Deep Convolutional Neural Networks): Because of their increased number of convolutional layers, DCNNs may learn more detailed characteristics. They apply additional layers of convolutional filters to the input image in order for the network to learn more abstract and sophisticated information.

6. Autoencoders: Autoencoders are a DL approach used to reduce dimensionality and learn unsupervised features. The network is programmed to reconstruct the original image from the compressed one, and this is how they work. The reduced representation can then be used for classification.

7. GANs (Generative Adversarial Networks): GANs are a DL technique that employs a generator and a discriminator network. The generator element produces false samples, whereas the discriminator element attempts to distinguish between them. Both networks are trained, with the former aiming to deceive the latter during the classification process. GANs can be used to identify satellite photos by producing additional samples and increasing the stability of the classification model.

8. LSTMs (Long Short-Term Memory Networks): RNNs are a method for dealing with the vanishing gradient problem. They use gating techniques to recall or forget particular hidden states at specific periods in order to capture long-term dependencies in sequential data.

9. (ResNet) Residual Networks: ResNet uses skip connections to overcome the vanishing gradient problem, making them a subtype of deep convolutional neural

networks. They work by allowing the network to learn residual features, which are then integrated with the input data to produce the output. As a result, the network can learn more nuanced and sophisticated features than typical DCNNs.

10. Capsule Networks: Capsule Networks, as a DL technique, can cope with spatial interactions between features. Capsules are neural networks that encode the possibility of an entity's existence as well as its properties. By integrating capsules into higher-level entities, the network can then learn spatial connections between features. Table 1 gives a detailed analysis of how the researchers used AI models on satellite images to detect landslides.

Table 1. AI models on satellite images to detect landslides

Data	Objective	Pre-process	Model	Metrics
Sentinel-2 Imagery [41]	To detect landslides investigates the viability of an integration architecture comprising a DL network and rule-based object-based image analysis (OBIA).	Not Mentioned	ResU-Net-OBIA	P–73.14%, R – 80.33%, F– 76.56%
Bijie Landslide Dataset [42]	To improve landslide detection, satellite imagery with scene classification should be used. By creatively integrating a focus mechanism into the model, successfully obtain data from satellite imagery.	Image Enhancement	Distant Domain Transfer Learning	A - 96.03%
LRSTTC [43]	Two approaches are described for the identification and segmentation of new and old landslides, and ice avalanches, namely Mask R-CNN and transfer learning Mask R-CNN.	Resize Annotation	Mask R-CNN	mPA – 87.71% mIoU –77.94% P– 81.18% R–78.47% F – 79%
Sentinel-2A [44]	Creates the squeeze-and-excitation network (SENet) as a channel attention mechanism for use in the feature fusion portion of U-Net, and it builds an attention U-Net landside extraction model by integrating SENet with U-Net. Sentinel-2A images are used to train the network.	Atmospheric Correction Annotation Augmentation	Attentional U-Net	F- 93.53% P - 93.19% R - 94.61% mIoU -94.30% Kappa -93.30%.
Recent Landslide Database (RecLD) [45]	Provides a unique machine-learning and deep-learning strategy for identifying normal-terrain landslides utilizing integrated geodatabases.	Layer Derivation Landslide Inventory	DCNN-11	A – 89.32% P - 92.58% R - 85.07% S – 93.43% F1 – 88.66%
Multiple Databases [46]	Using powerful machine and DL techniques, mapped the landslide susceptibility areas in the Garhwal Himalaya	Information Gain Ratio	DL Neural Network	R – 83% S - 96% Kappa - 81% P – 93%

	region. Five different models were studied and compared.	Multi-Collinearity Analysis		AUC– 92.5%
Bijie Landslide Dataset [47]	Create the Dynahead-Yolo model, integrated the YOLOv3 framework's space, scale, and task-aware attention mechanisms. Improves the capability to decode landslides in complicated background settings by focusing on the finer details of landslides images with varying proportions.	Augmentation Annotation	Dynahead-Yolo	F1 - 87 % P - 87.17% R - 87.56% mAP – 85.53%
Bijie Landslide Dataset [48]	Introduce a unique UNet model for autonomous identification of landslide, in which the reversed image pyramid features (RIPFs) are modified to compensate for the information loss resulting from successive convolution and pooling.	Radiometric Correction Orthographic Correction Atmospheric Correction Image Fusion	RIPF-UNet Model	F – 92.34 % P - 89.91% R - 94.90% A – 97.25%
GF-2 Remote Sensing Images [49]	Completed the task of landslide susceptibility mapping in Hanyin County, China using the LSNet model. LSNet's results were evaluated against those of SVM and the kernel logistic regression model.	Cropping Annotation	Landslide Net (LSNet)	A – 95% P - 95.1% R – 95.1% S – 94.9% F1 – 95.1%
SAR Images [50]	To produce multichannel images for reliable categorization, not just of the target area but also of their surrounding areas. The best multichannel CNN architectures for landslide classification of SAR images are determined after a thorough analysis of the available structures.	Cropping Data Balancing	Multi-CNN	A – 74% P - 66.5% R – 78.2% F – 71.9%
A-Accuracy, R-Recall, P-Precision, mIoU-Mean Intersection of Union, F-F1 Score, S-Specificity, mAP-Mean average precision, AUC-Area under curve				

VIII. CHALLENGES

The following are the most important issues with existing DL-based landslide detection techniques:

A. *Timely acquisition.*

Providing a viable solution for near real-time threat identification is a big issue that can only be handled by integrating AI algorithms' capabilities.

B. *Recognising the landslide's spatial, spectral, and temporal characteristics is difficult [51]:*

The spatial, temporal, and spectral aspects of landslides may be difficult to determine. The outer look of a landslide can vary greatly depending on the surrounding weather, geology, and geography. Because of the aforementioned influences, implementing a universal mechanism for identifying landslides is difficult. Deep and shallow landslides have a large spatial disparity. Because of the frequent and noticeable variances in landslide features, identifying landslides with basic criteria is critical. Because landslides can take many forms, broad rules must be used to classify them. Some landslides that have recently occurred can be easily identified as such. The boundary between the uninjured land surface and the failure areas is obvious in shallow and modest landslides (such as debris flows). However, in the case of large and complex landslides, the boundary between stable and failed areas is difficult to predict. Transport depletion and deposition zones are examples of failed places. It may be difficult to detect landslide borders in older landslides. Due to the wide variety of landslide occurrences, not all landslides are easily and clearly recognizable in any satellite image.

C. *Inadequate landslide images:*

A lack of training data is one of the most prevalent impediments to successfully deploying a data-driven model based on DL. This is due to the need for a huge volume of high-quality data during the essential training stage of an AI algorithm.

D. *Poor spatial resolution [52]:*

For landslide detection, high-resolution images are required for model construction in AI frameworks. High-resolution data is required for landslide detection and instance segmentation over landslide images. VIA (VGG image annotator) class labelling relies on a clear delineation between the failure region (i.e., deposition area, depletion) and the unaffected landscape. Because of the landslide's age, it's difficult to distinguish what's a landslide and what isn't. Improving the reliability and accuracy of landslide recognition necessitates consideration of both image resolution and landslide pattern.

E. *Security and authenticity:*

The open nature of the communication medium presents severe trustworthiness and safety concerns. Image authentication of space-borne and open-source images addresses challenges of image integrity, authenticity, and provenance verification. Space-borne images often analyse emitted and reflected radiation from a large distance to record, monitor, and identify the physical features of a location. Digital images, on the other hand, may now be quickly manipulated, copied, reproduced, and disseminated at low cost due to advances in technologies and the ubiquitous accessibility of the internet. The advancement of network technology has had a tremendous impact on data security and privacy. To secure the digital content from future dangers, content authentication, duplicate prevention, and copyright protection are essential.

F. *Class imbalance [53]:*

Using satellite images to detect landslides is a common issue. Class imbalance occurs when the training data contains a disproportionately small number of examples from one class (say, landslides) compared to the other class (say, non-landslides). In other words, there is an imbalance in the training data between the classes. When attempting to detect landslides, the number of images that do not contain a landslide is typically significantly greater than the number of images that do contain a landslide. This is because landslides are uncommon in comparison to the overall area under study. Due to the class imbalance, the ML model may be biased towards the majority class (i.e., non-landslide), resulting in poor identification of the minority class (i.e., landslide). Consider an AI model that has good accuracy in differentiating non-landslide areas but low recall in predicting landslide locations since it was trained on imbalanced data. That instance, the algorithm may properly identify most spots that are not prone to landslides while ignoring other prone areas. There are several techniques for dealing with the class imbalance problem in landslide detection. Common strategies for achieving this balance in training data include oversampling the minority class, undersampling the majority class, and creating artificial minority samples. It is also conceivable to use cost-sensitive learning approaches during training to give the minority class more weight in the learning process.

IX. Conclusion

In conclusion, the application of AI-based algorithms to the analysis of satellite images for the identification of landslides is an intriguing and FAST-DEVELOPING topic with enormous potential for enhancing the ability to track and MINIMIZE landslide hazards. In this review, we take a look at the numerous AI strategies that have been applied to the problem of landslide detection and discuss some of the main elements that may influence the reliability of these techniques. This technique can assist prevent mortality and property loss, and MINIMIZE the ecological effects of landslides, by giving precise and early information on landslide hazards. However, there are still some obstacles that must be overcome, such as the requirement for high-quality and balanced data. But AI models may gain insight from past data, these models can get better over time, resulting in more accurate landslide detection. In this article, the state of AI-based landslide detection using satellite images has been well-surveyed. The advancement of this field of research has the potential to save the lives of individuals who live in landslide-prone areas by allowing for better monitoring and management of landslide risks. Also, we're hoping that the findings of this survey will guide researchers in the right direction as they continue to explore this important area.

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