International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 16s, 2025
https://www.theaspd.com/ijes.php

# Two-Phase Architecture For Detection Of Landslides Via Satellite Images

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***Abstract***
*Landslides are severe geological phenomena that often result in the loss of human lives, destruction of property, and interruption of economic activities. The use of image-based techniques in landslide investigations plays a pivotal role in the assessment of vulnerability to landslides and risk. Satellite imagery has been extensively used in practical applications for conducting such studies; yet, it requires substantial allocation of labor and time constraints. This paper presents a novel approach for the detection and segmentation of landslide zones using satellite pictures. The proposed framework is built on a two-phase data-driven methodology that utilizes image analysis techniques. During the first step, the Faster-RCNN technique is used to train an object identification model to identify the precise position of landslides within satellite pictures on a large scale. The suggested and displayed boundary boxes depict the locations of each landslide. The second stage involves the partitioning of the satellite photographs into smaller images determined by the location information that is supplied by the bounding boxes. After that, a method called boundary identification is used to determine the border parameters of each loess landslide that has been found. This helps to enhance the effectiveness of the segmentation procedure. Because additional inception blocks with dilatation were included in the construction of the segmentation U-Net, its effectiveness in landslide segmentation has significantly increased as a direct consequence. It is well known that separating loess landslides into their parts is a difficult task. This is mostly attributable to the intrinsic qualities of boundary information that is ambiguous. The novel framework is tested in comparison to the conventional U-Net as well as other modern benchmark landslide segmentation methods. The results of the computer analysis show that the suggested structure achieves a level of accuracy in dividing up loess landslides that is much higher than that achieved by the other benchmarking methods that were looked at.*

***Keywords:*** *Loess landslide, data-driven methodology, Object detection, RCNN technique Image segmentation, Boundary detection, Data fusion.*

## 1. INTRODUCTION

Landslides are an instance of geohazard that have the potential to produce cascading effects, which may result in major destruction of human life as well as natural resources, infrastructures and buildings situated on steep terrain. [1]. A typical landslide often encompasses the displacement of a conglomeration of detritus and boulders, as well as the collapse of slopes, which may be investigated by factors such as precipitation, fast snowmelt, seismic activity, and volcanic emissions [2]. Loess, a silt-based material created by wind-blown dust, covers 10% of Earth's territory. Loess-dominated landslides are collectively called loess landslides. Mudstone is usually present in loess landslides. Loess landslides are tiny and short-lived, caused by fluidization and melting. Most loess plateau landslides are loess or loess bedrock. Loess landslides have a sliding surface within the stratum. The sliding surface of the loess bedrock landslide is often located at the boundary between the bedrock and loess layers [3]. Loess collapses are always caused by water, comprising irrigation, tectonic precipitation, and groundwater dynamics. Hence soil structure and porosity play a vital role in the cause of landslides. Despite the great progress made in scientific studies on the identification and segmentation of landslides, there is a significant gap in attaining full automation of image-based analysis for landslides.
Image-based landslide research is vital for both understanding the processes of landslides and decreasing the harm they cause. Typical tasks include detecting landslides, classifying them, segmenting them, extracting features, and performing geomorphological analysis [4]. Satellite images show the extent of landslides. Landslides reveal rock and dirt, altering picture sub-region pixel brightness. Landslide distribution and genetics affect picture characteristics [5]. The brightness, strong contrast, and scar-like margins of landslide-induced

images are crucial for interpreting them visually and semiautomatic or automated geohazard classification [6]. Remote sensing uses satellite image reflectance information (pixel values) to assess the identification of changes, land surveillance (urban planning trends), and vegetation study.
Satellite imagery is voluminous due to its size (depending on spatial resolution) and definition (depending on spectral resolution). Sensor features including resolution of space, collection date, the use of georeferencing, along with cloud cover are included in satellite picture information. Satellite picture AI pipelines need this data to analyze and manage. The process of obtaining satellite imagery via the use of optical sensors is illustrated in Figure 1.

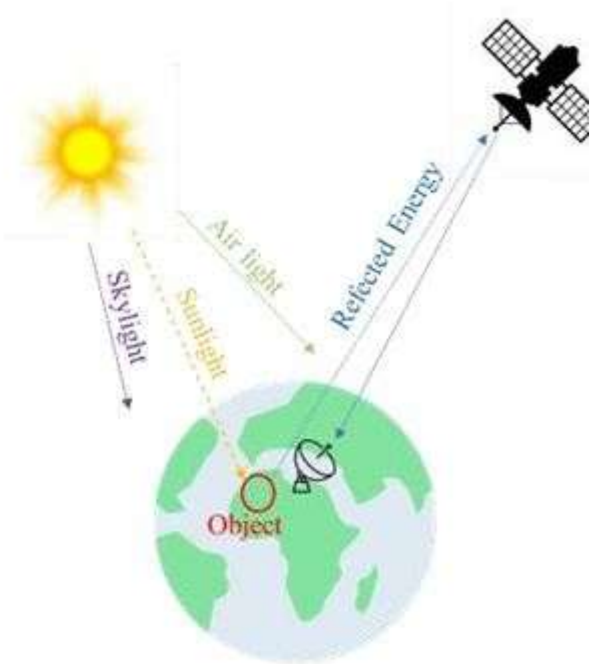


**Fig.1. Satellite picture acquisition using optical sensor**

Approaches based on artificial intelligence, remote sensing, along human-centric detection may be grouped as three distinct types of research that have been done in the past on the identification and categorization of landslides via the use of satellite pictures. The bulk of the work for human-centric detection is predicated on the assessment of specialists based on satellite or other image analysis, with field surveys subsequently serving to increase the dependability even more [7-9]. For instance, satellite imagery is used to conduct many case studies to detect landslides that were caused by earthquakes. On the other hand, human-centric landslide area identification is very labour-intensive and ineffective.
Remote sensing technology has advanced rapidly, enabling semiautomatic landslide detection and improving efficiency. Airborne InSAR or LiDAR data is used for most of the work. In [10], InSAR data was processed using continuous scatter interferometry to identify and categorize landslides as flows, falls, or slides. High-resolution LiDAR data to identify landslides and estimate risk using morphological analysis [11]. A persistent homology technique for LiDAR-derived digital topography model landslide detection [12] is employed. All three methods of remote sensing have produced very accurate landslide detection, which assists with both localization as well as identification. These findings have shown promise as a tool for remote monitoring. In recent years, deep learning algorithms in artificial intelligence (AI) have proven useful for assessing landslide aspects using massive imagery sets. Convolutional neural networks, often known as CNNs, are an innovative technique for processing image data and obtaining a wide variety of information from those images. CNNs have shown to be useful in a variety of industries, including the energy sector [13-15].

## 2. LITERATURE SURVEY

Landslides, which are among the most extreme threats [16], are initiated by human activities, geology, hydrology, and geology. Seismic activity, heightened precipitation, and anthropogenic activities all possess the capacity to trigger catastrophic landslides. An evaluation by Landslides of heightened intensity would manifest in conjunction with increasingly severe weather phenomena induced by climate change. Prodigious landslides possess the capacity to induce substantial infrastructure destruction and lead to notable loss of life. Prediction and management of landslides are thus critical to prevent and mitigate the devastation that can ensue as a consequence of this danger. In the absence of reliable precursory data, however, real-time landslide timing forecasting is frequently difficult to achieve [17].

Being susceptible mapping, which is similar to landslide prediction [18], considers "where" collapses are most likely to occur in the future. The term "susceptibility" pertains to the probability that landslides will transpire at a given site as a result of specific geological and environmental characteristics [19].

Hazard management begins with landslip susceptibility (LSM) mapping. This is because it calculates landslip probabilities and determines landslip zones. Additionally, it may provide scientific catastrophe management advice. Landslide susceptibility mapping uses environmental factors. Geographical terminology, land use vegetation cover (LULC), and rainfall have been linked to landslides in LSM research. Slope stability is affected by vegetation cover, which enhances slope materials cohesion and lowers pore water pressures via transpiration, as well as slope aspect, which affects rainfall and sunshine accumulation [20]. Landslides are distributed by geology, notably rock hardness. Slope failure decreases with rock hardness. Hard rock reduces landslides [21]. Several methods may reveal underlying patterns between landslip episodes and environmental circumstances, allowing exact susceptibility prediction. LSM has been addressed using several qualitative and quantitative methodologies in recent years. Knowledge-based qualitative methods use geomorphologist expertise. These methods are being superseded by quantitative ones. Data-driven or physical-based quantitative methods exist.

Considering sedimentary soils and rocks around landslides is important [22]. Data-driven LSM techniques have improved thanks to GIS, analytical algorithms, as well as machine learning. Random forests, logistic modelling, synthetic neural networks, and the backing vector machines function in LSM. LSM alternatives include hybrid models that combine statistics learning and machine learning.

Landslides harm lives and destroy resources. Natural disasters cost money to reconstruct structures, lose property value, disrupt transportation, treat injuries, and destroy timber and fish populations. Landslides change water quality and quantity [23]. Landslide detection and mapping are usually done in field investigations as part of a geomorphological study. Identifying past landslides is difficult with this method. AI-based autonomous landslip detection is crucial to landslip prevention. Many geomorphological features suggest landslides. LRSTTC has expert- and field-verified landslides. FORMOSAT-2[24] sells affordable, high-resolution photographs from Taiwan. FORMOSAT-2 photos assist Taiwanese landslip monitoring. The optical satellite FORMOSAT-2 has four multidimensional bands. Panchromatic groupings are 2 meters, and multidimensional 8 meters. The images are 8-bit radiometric. Geographic coverage maps accompany each photo. Write "ground truth" on the land cover maps. Each image pixel is categorized precisely. Manually manipulated photographs show land use. Model land cover includes water, vegetation, farms, and cities.

The majority of the research in the literature compares machine learning and statistical techniques, whereas just a few compare CNN to more conventional methodologies [25]. Filling the void will need research into the available options and a quantitative, methodical evaluation of their relative merits. To test models and get reliable results, LSM research often uses comparative studies. Due to their fundamentally different approaches to data organization, a comparison between CNN and more conventional machine learning methods is crucial. It is essential to have an ample supply of training samples when applying deep learning to the job of identifying catastrophe areas. However, the conditions under which SAR images are taken vary with time, as the seasons do. It may also be difficult to rapidly gather a large number of training cases annotated with the proper class labels after a disaster has occurred. The image features of small-proportion photographs are more difficult to retain than the visual characteristics of large- proportion pictures due to the thickness of network connections and the increase in the area of reception. This makes the model more likely to misjudge or even completely miss major landslides than it is to correctly predict tiny avalanches. There is a considerable chance of false detection when trying to find landslides in locations with complicated backdrops if the area's spectral properties are similar to those of disaster zones. To address this problem, we suggest a tracking anomaly system capable of distinguishing out-of-the-ordinary photographs from ordinary ones.

Deep learning on picture data has been widely investigated in landslide investigations. The contour-based semantically segmented deep learning model detects and segments landslides [26]. Using pre- along with post-landslide aerial pictures. A deep CNN model dubbed Land CNN to segment landslides better than existing benchmark algorithms. From satellite pictures as well as digital elevation model data, attention-boosted CNNs to identify landslide areas. In general, deep learning methods have improved pixel-level landslide detection and prediction[27,28].

In conclusion, the existing methods that are used to identify and categorize landslide zones have shown some encouraging signs of improvement but also contain several drawbacks. To begin, the tasks of landslide detection and segmentation are carried out independently in the majority of the case studies that are included in the published research. When it comes to segmentation jobs in particular, a considerable amount of manual work is necessary to find a landslide zone from a huge number of satellite photos using the judgment of specialists. Second, almost all of the uses of deep learning techniques on photos of landslides are for the aim of detection. For future geohazard mitigation, they lack crucial information such as exact boundary data regarding the target area. Furthermore, identifying the ground fact as the region impacted by the collapse pixel-by-pixel requires significant time and effort. This indicates that the possibility of employing completely automated methods is restricted as a result of the complexity and enormous expense of the procedures involved in the data pretreatment process. The primary objective of this study is to design and implement a system for the completely autonomous identification and segmentation of loess landslides using satellite imagery while simultaneously guaranteeing that it is both effective and accurate. Additionally, it is desired to attain pixel-level precision fragmentation of the landslide zone. This will make it possible for us to derive the limits of the landslide region for the sake of risk prevention.

The aforementioned explanation leads to a two-phase based on pictures data-driven paradigm in this research. First, the Faster-RCNN system is retrained to identify the landslide area using transfer learning. Second, using the detection bounding boxes, a partitioning U-Net incorporating data fusion segments the landslide zone and makes pixel-level predictions. Benchmark segmentation methods like U-Net and FC-Dense Net are also compared. This study's primary contributions involve the following details. The proposed methodology combines detection along with segmentation algorithms in a unified framework to autonomously identify and delineate the landslide zone. Furthermore, this strategy represents a novel use of deep learning techniques for achieving more accurate segmentation of the loess landslide area. The work at hand presents increased technological complexity because of the limited variation in images between the area affected by landslides and the other portions of the picture. Additionally, the anticipated limits of the landslide zone are extracted to identify the high-risk area, and to mitigate potential geohazards.

## 3. Proposed Methodology

Using a two-phase framework, the primary objective of this study is to achieve completely automated identification and classification of a soil landslide zone from many different satellite photos. This will be accomplished by analyzing the images in two separate phases. The two-stage architecture proposed here is shown graphically in Figure 2. First, we trim a 2000x2000px sub-image from satellite images to help with our preliminary identification of the loess collapse zone. Every pixel here represents a 0.49 by 0.49 m section of the landslide zone. We identified the level of gravity of the avalanche zone with the help of geological professionals, and we utilized it as the focus point for the photo cropping. Next, we classify every loess landslide as the gold standard and utilize transferred learning to educate yet another Faster- RCNN model for object identification. The first stage of the process produces a false prediction that a soil landslide will not occur, as well as a box with borders that pinpoints the location of the soil collapse zone inside the original 2000 by 2000-pixel input image. During the second step, we begin by cropping a sub-image with dimensions of 800 by 800 pixels. The centre of this sub- image is determined by the centre of the boundary rectangle that was generated during the first phase. Then, within the 800x800-pixel cropped image, we manually locate the landslide zone using a segmentation U-Net we trained using data fusion. The area affected by the soil landslide has been predicted down to the pixel. Furthermore, we extrapolate the bounds of the forecast result to display the landslide boundaries, providing important data for averting potential geohazards.

### 3.1. Soil-Based Landslide Detection with Faster CNN

The Faster-RCNN method belongs to the third generation of the RCNN family. It is designed to accurately

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predict both the description of the target item in an input picture and the existence of the object inside a proposed candidate area. In contrast to the first and later generations, such as the RCNN as well as the Fast-RCNN, the Faster-RCNN presents a CNN- based alternative that is referred to as the regional proposal network (RPN). This network and the CNN-based recognizing network, exchange their respective biases along with weights with one another. The use of this technology results in significant improvements to the effectiveness of real-time object recognition regarding velocity as well as precision. These gains may be seen in the effectiveness of the process. Figure 1 provides a visual depiction of the architectural components of the RCNN method, which is the faster of the two.

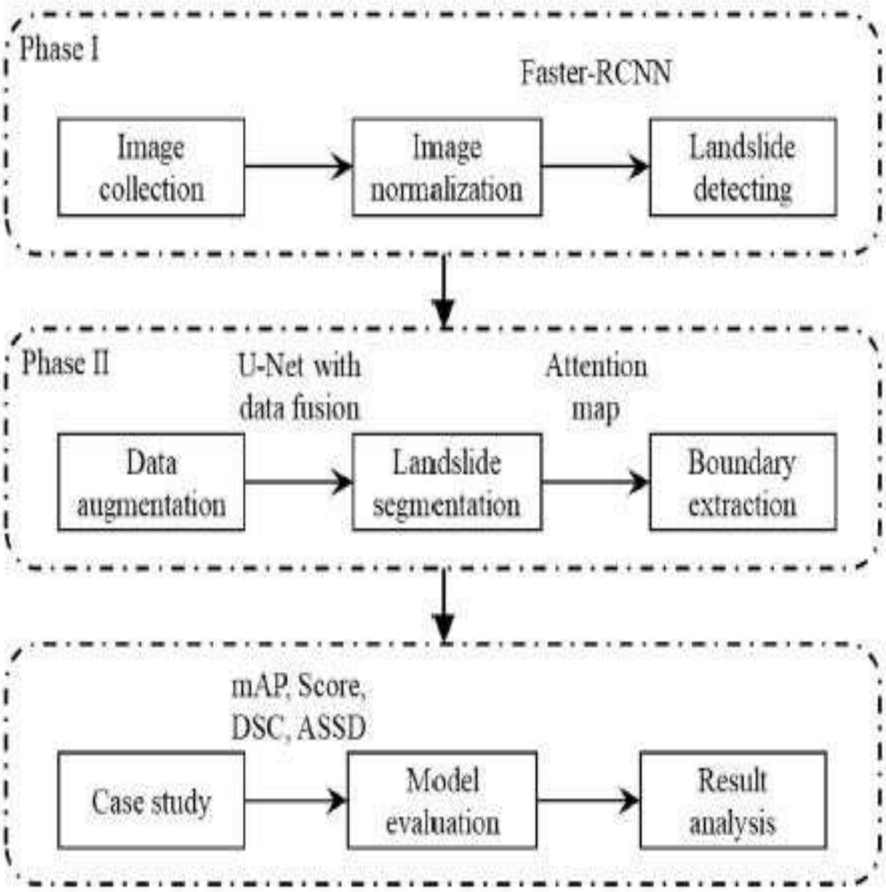


**Fig.2. Structure of the two-stage scheme**

The Faster-RCNN uses the underlying network, RPN, and ROI pooling to identify objects end-to-end. Figure 2 demonstrates how the Faster-RCNN generates attribute activation mappings for an annotated image by using a large number of convolutional layers in common. These shareable convolutional layers are often implemented using pre-trained CNN baseline layers like VGG-16. After that, the RPN determines, with the help of bounding box regression, if the target object is in the foreground or the background, and it suggests the starting region, which indicates its presence in the image. After ROI pooling analyzes these ideas, two completely linked layers are layered. The first layer that is fully connected predicts item bounding box locations using a bounding regression box. The second fully linked layer uses SoftMax classification to identify item subcategories. A score that indicates the likelihood that a candidate item matches a sub-category is one of the outputs that a Faster-RCNN technique generates, along with a vector that provides the corner position, width, and height of the projected bounding box.
Training of the categorization and regression components of the Faster-RCNN architecture is accomplished by the use of various loss functions as well as equations. These components are responsible for generating

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region suggestions, wherein the object class, as well as relative location, are recognized.

$$L(\{Prob_i, BVect_i\}) = \frac{1}{N_{cl}} \sum_i L_{cl}(Prob_i, Prob_i^*) + c \frac{1}{N_{lc}} \sum_i Prob_i^* L_{lc}(BVect_i, BVect_i^*) \quad (1)$$

The terms $N_{cl}$ and $N_{lc}$ are used to normalize the two loss functions, $L_{cl}$ and $L_{lc}$, respectively. The combination parameter 'c' is utilized in this context. The index i denotes the starting point in a mini-batch, and the $Prob_i$ value indicates the predicted probability that the anchor i is an item. In addition, $BVect_i$ is a vector that represents the four individualized coordinates of the anticipated bounding box. $BVect_i$ is a representation of the predicted bounding box. $L_{cl}$ and $L_{lc}$ are abbreviations that stand for "losses associated with classification" and "losses associated with localization loss," respectively. Following is a mathematical representation of the classification loss that may be used:

$$L_{cl}(Prob_i, Prob_i^*) = -\log[Prob_i\, Prob_i^* + (1 - Prob_i)(1 - Prob_i^*)] \quad (2)$$

In the above scenario, when the value of $P_i$ is negative in nature, the likelihood of the fundamental tag $P_i^*$ is determined to be 0. Alternatively, in the case when $P_i$ is a positive number, the product of $P_i^*$ is equal to 1. Mathematical expressions for the localization of regression loss look like this:

$$L_{lc}(BVect_i, BVect_i^*) = \sum_{i \in (p,q,r,s)} SM_{L1}(BVect_i - BVect_i^*) \quad (3)$$

Let's say p and q are the location of the box's center, and r and s are its width and height. The smoothing function may be expressed mathematically as:

$$SM_L(x) = \begin{cases} 0.5x^2, & if\ |x| < 1 \\ |x| - 0.5, & otherwise \end{cases} \quad (4)$$

where x is the value of predicted bounding box. This study uses Faster-RCNN to identify landslides because its region proposal approach does regression and classification concurrently. The bounding boxes show the loess landslide's relative position, and the certainty score estimates its likelihood. Thus, the Faster-RCNN method uses U-Net to automatically focus on a tiny portion of the picture and enhance segmentation.

**3.2.U-Net for landslide segmentation**

In recent years, CNNs have shown remarkable success in tasks such as image classification, object recognition, and pixel-wise segmentation. On publicly available datasets, CNNs provide much better results than graph-cut and multi-atlas segmentation. There are three main factors that contribute to CNN's success. CNNs use stochastic descent optimization to learn particular visual characteristics to a given domain. Secondly, all pixels share learned kernels. Last but not least, images are used in convolutional procedures. Segmentation problems are a strong suit for full convolutional networks (FCNs) such as the U-Net architecture and Deep Medic.

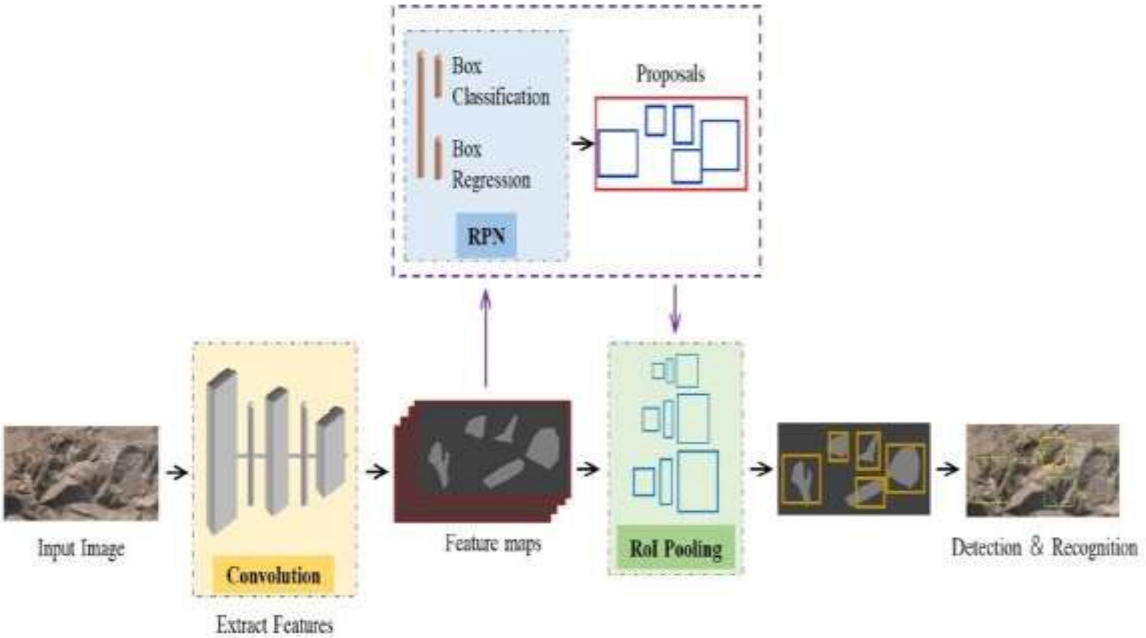


**Fig.3. Faster-RCNN algorithm schematic diagram**

The U-Net follows an encoder-decoder structure. It has been widely recognized for its exceptional performance in several intricate picture segmentation tasks, positioning it at the forefront of the field. The design of the system is characterized by its symmetry, consisting of two primary components: encoder networks and decoder networks. Like most convolutional neural networks (CNNs) used for image recognition, the encoder network uses convolutional layers to pull out features from the incoming image. These features are then down-sampled into latent layers, resulting in a more compact feature map.

The latent vector located in the centre captures the whole visual context. In the meantime, the decoder network conducts up-sampling operations to align the output resolution with the dimensions of the input picture, hence facilitating accurate pixel-level prediction for the segmentation process. Furthermore, the use of skip connections facilitates the transmission of data between the corresponding resolution of the two components, hence enhancing the network's capacity to effectively segment pictures with greater accuracy.

### 3.3. Functions for loss in segmentation

All segmentation algorithms that were examined demonstrated identical performance in the pixel-level binary classification challenge. The objective of this job is to predict the label of each pixel in photographs of size 800 × 800, to classify whether the pixel belongs to the forefront (loess landslide zone) or the background (non-landslide region). The binary cross-entropy reduction function was used for all the methods examined in this study. It may be formally described as follows:

$$L_{EnCrs} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{2} y_i^c \log (P_i^c) \quad (5)$$

The variable $P_i$ represents the likelihood of pixel i being classified as either a loess landslide zone or a non-landslide region. The variable $y_i$ represents the fundamental truth label of each pixel "i". The variable "N" represents the entire number of pixels in the given picture, which is 800 × 800.

### 4. Experimental Evaluation

We created a two-phase satellite image framework to automatically identify and segment loess landslides. The network was trained to identify and segment loess landslides using supervised training. The evaluation data showed that the suggested framework outperformed existing state-of-the-art algorithms in loess landslide identification and segmentation. The suggested two-phase structure offers three main benefits. First, it automatically detects and segments satellite photos in one step. Detecting the loess landslide zone in a wide satellite picture is faster and easier using the well-trained U-Net. Second, it allows pixel-level prediction of loess landslide zones, which is necessary for precise range estimate. Estimating this geohazard and its future recurrence depends on segmentation results. We retrieved loess landslide limits as well. The findings may help geologists detect and categorize landslide types.

The literature study shows that loess landslide identification and segmentation is harder than other landslides. First, brightness, color, and surface information in loess landslide zones is more similar to non-landslide regions. This reduces both the detection as well as segmentation efficiency of all strategies in this work, and our landslide detection testing accuracy was 0.5 mAP

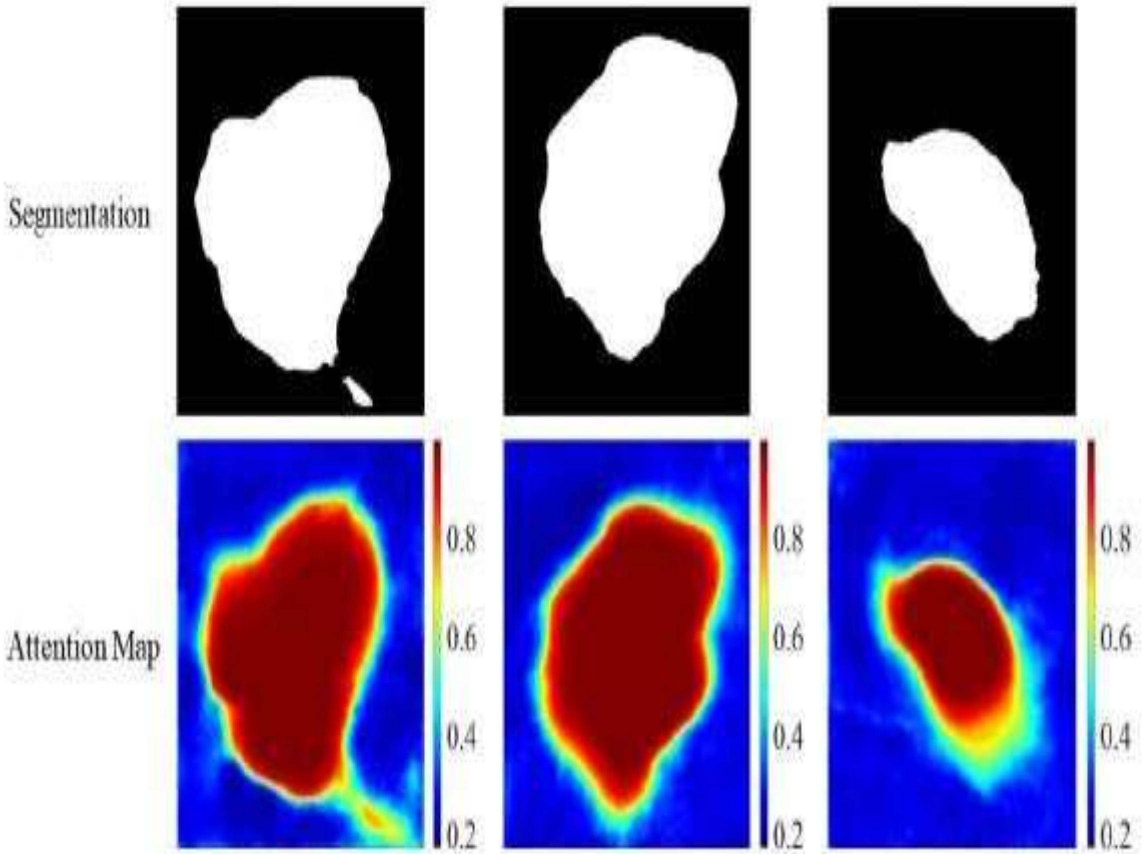


**Fig.4. Final decoder network layer produces probability maps.**

. Because loess collapses are hard to see in huge satellite photos, data collecting takes longer and involves more manpower. So, they enhanced their splitting accuracy in a comparable spectrum as ours but in a bigger picture. Another segmentation drawback is the absence of runout- direction region boundaries.

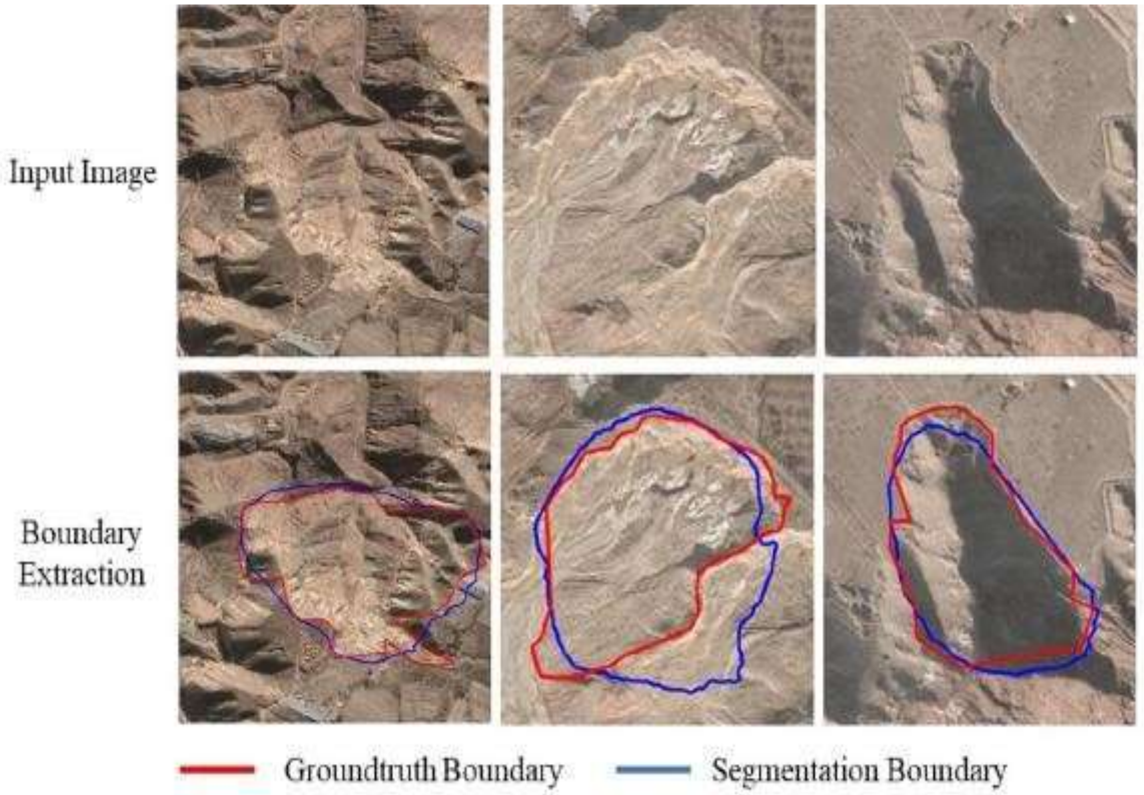


**Fig.5. Segmentation of loess landslides with ambiguous borders**

Experts set the runout direction ground truth limit, which may vary in a narrow range and lead to less exact standards while training deep neural networks. Therefore, border distance errors may be higher. As seen in Fig. 5, bigger ASSD values may make deep neural networks' prediction difficult due to inadequate boundary information. Furthermore, source area separation fails. The segmentation identifies just the individual pixels of the loess landslide zone, not the source and runout areas.

**Table 1. Comparison of Existing Methods with Proposed Strategy**

| Strategy | Area | Occurrence % | Standard Error % | Frequency Ratio | Prediction Accuracy |
|---|---|---|---|---|---|
| SVM | 0.855 | 0.45 | 0.08 | 0.72 | 0.7 |
| ANN | 0.945 | 0.36 | 0.07 | 0.71 | 0.75 |
| BAGGING | 0.827 | 0.41 | 0.06 | 0.69 | 0.65 |
| PROPOSED METHOD | 0.857 | 0.37 | 0.07 | 0.68 | 0.91 |

The absence of a clear border between the loess landslide subregions is the key reason. Thus, applying this approach to loess flow, loess-bedrock interface, and loess bedrock plane landslides would result in the same issues.

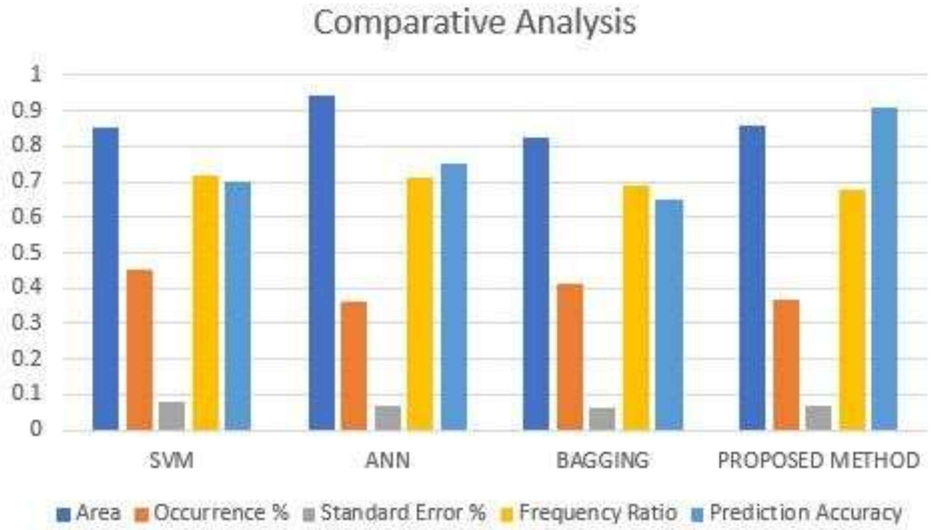


**Fig.7. Comparative Analysis of Existing Methods with Proposed Methodology**

Table 1 provides with the comparison of existing approach with the proposed strategy and is illustrated in figure 7, which clearly depicts proposed method outperforms the state of art methods.

## CONCLUSION

A unique two-phase data-driven system for automated loess landslide identification and segmentation using satellite pictures is presented in this research. The framework's initial step uses the Faster-RCNN technique to find loess avalanche geological features and name them with bounding boxes. Transfer learning was used over the pre-trained Faster-RCNN algorithm in this investigation. Loess landslide picture segmentation and pixel-level prediction were examined in the second phase. To improve segmentation, a 2D U-Net with origination blocks was used. To identify loess landslides more efficiently and visually, segmentation boundaries were recovered and compared to geological expert ground truth labels.

The suggested architecture automatically identified and segmented the loess landslide zone, ensuring a high-quality border and total area prediction compared to powerful single identification or segmentation techniques. The updated U-Net's extra inception blocks enhanced features and segmentation performance. The suggested system is better for loess landslide identification and segmentation than previous related articles. Future visualization of segmentation U-Net latent characteristics will aid landslide hazard decision-making. Deep neural network mechanisms (e.g., U-Net) will be our key research focus in the future. To execute multi-objective segmentation, we want to build stronger segmentation algorithms. It can determine the source location from the runout, which improves landslide research.

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