




A New Mask R-CNN-Based Method for Improved Landslide Detection

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Abstract—This article presents a novel method of landslide detection by exploiting the Mask R-CNN capability of identifying an object layout by using a pixel-based segmentation, along with transfer learning used to train the proposed model. A data set of 160 elements is created containing landslide and nonlandslide images. The proposed method consists of three steps: augmenting training image samples to increase the volume of the training data; finetuning with limited image samples; and performance evaluation of the algorithm in terms of precision, recall, and F1 measure, on the considered landslide images, by adopting ResNet-50 and 101 as backbone models. The experimental results are quite encouraging as the proposed method achieves precision equals to 1.00, recall 0.93, and F1 measure 0.97, when ResNet-101 is used as backbone model, and with a low number of landslide photographs used as training samples. The proposed algorithm can be potentially useful for land-use planners and policymakers of hilly areas where intermittent slope deformations necessitate landslide detection as a prerequisite before planning.

Index Terms—Convolutional neural networks (CNNs), global positioning system (GPS), landslide detection, Mask R-CNN, region based convolutional neural networks (R-CNN), terrestrial laser scanning (TLS), transfer learning.

I. INTRODUCTION

LANDSLIDES or mudslides are an extensive phenomenon, resulting in huge upheavals worldwide with a great frequency [1]–[3]. It is a significant hydro-geological threat affecting large areas of the world, and in particular the India country, including the Western Ghats, North-eastern hill areas, Himalayan regions, etc. The Northwest Himalayan regions of India, incorporating Himachal Pradesh, Jammu & Kashmir and Uttarakhand, are known for highest landslide hazard prone areas. Many heritage temples and Hindu pilgrim sites such as Badrinath, Kedarnath, and Kailash Mansarovar are situated in

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these upper Himalayan regions. Landslides occurring in Himalayan regions have been causing considerable damages to archaeological sites and severe loss of lives for many years. The world heritage site most vulnerable to landslides includes Changu Narayan Temple, Machu Picchu, and the Darjeeling Himalayan Railway.

Climate changes and anthropic activities have affected many archaeological sites in these regions in a severe way. Some of them are under an even bigger risk because of surrounding slope instability, which can activate landslides and compromise the place integrity. Many researchers have studied the landslide susceptibility, hill slope stability, risk management assessment mapping and remote sensing based heritage site management in the hilly regions worldwide, and in the Himalayan as well as in India [3]–[5].

A volume of research works across the world have studied the phenomena related to landslide for the risks related to cultural heritage sites and attempted to assess their possible impact. Moreover, an International Programme on Landslides has been created, since March 2003 [6]. Major activities for landslide risk assessments, at three major cultural heritage sites in China (Lishan, Xian), Peru (Machu, Picchu) and Japan (Unzen volcano), were reported in [7]. Analysis for the threat posed to cultural heritage by landslide and avalanches were carried out for Upper Svaneti region in Georgia. Factors, such as slope, land cover, lithology, and snow avalanches were also used to generate a susceptibility map [8], [9]. As regards Italy, despite being a country relatively small in its extension, almost all types of natural risks, including earthquakes, landslides, volcanos, floods, and coastal erosions are present. Floods and landslides appear to be the major geological problems for Italian cultural heritage sites. An interesting study was carried out in [10] and [11], where an empirical geographical information system based method was applied to characterize the environmental hazards for identified heritage sites in Italy. India and Italy are among the countries with many archaeological sites under the risk of natural hazards such as landslides, subsidence, floods etc.

For this reason, we have carried out this joint work which presents a novel model for the automated detection of landslides from digital photographs of target hilly areas, acquired by unmanned aerial vehicle (UAVs), by using computationally efficient machine learning based methods. Moreover, the proposed model by its nature is easily exportable and applicable

to other areas of interest. In the last few years, various remote sensing data types have been used dealing with the monitoring of ground deformations, landslide assessment, post-wildfire burnt area assessment, heritage site and critical infrastructure monitoring [12]–[14]. These remote sensing data include: optical data; synthetic aperture radar (SAR) data; and light detection and ranging (LiDAR) measurements. Important literatures are available on various remote sensing modalities and the types of remote sensing data [12], [15]–[18].

Monitoring deformation of earth surface displacement and structures specifically during landslides can be investigated by utilizing several distinct types of methods and schemes [3], [12], [19]. Moreover, extensive literature survey also on landslide photographs, UAV images and digital photogrammetry can be found in many research papers [20]–[22]. The advantage of using UAV images lies in the ability to operate quickly and gather historical, monitoring and mapping data [23].

Over the years, many image-analysis-based landslide detection and assessment techniques were proposed for various types of remote sensing images [17], [24]–[26], with the landslide studies recently based on approaches like machine learning-based pixel and object-based image analysis [27], [28].

Detailed literature survey on application of machine and deep learning for landslide detection can be found in [29] and [30]. Benefits of deep learning on natural images as well as the remote sensing images along with its limitations can be found in [31], where convolutional neural networks (CNNs) have been utilized for extracting information from satellite optical images.

Yet, in order to retrieve remarkable results in landslide monitoring, machine and deep learning techniques require large amount of data. This is a major drawback because currently feasible dataset is not enough and is also unavailable in big quantity. Moreover, for landslide detection, exhaustive landslide dataset is required, which should contain images captured in distinct conditions. However, dataset collection, retrieval and annotation of these data are a key restriction during the overall landslide detection process. Additionally, it is an inconvenient and heavy task to retrieve high resolution data in the field of natural hazard management studies.

In this regard, since transfer learning and masking techniques have been efficiently used with distinct images, such as drone images, optical remote sensing images, drone aerial images etc., to perform object detection and instance segmentation, as explained in [32] and [33], the interest to understand their effectiveness if applied to landslide detection arises spontaneously.

With respect to the state-of-the-art, this article aims to present a new algorithm, which uses a Mask R-CNN [34], along with transfer learning to train the proposed model, in order to detect landslide occurrences with only fewer object images. The major contribution of the work presented in this manuscript is precisely the use of a pre-trained CNN model for the detection of landslides from photographs. Pre-trained models of CNNs, such as ResNet-50 or ResNet-101 chosen in our case, have demonstrated to not require large set of data for training, as the method can exploit the pre-trained learning model performance. Therefore, the proposed Mask R-CNN model can give reasonably good results using very small dataset.

TABLE I
OVERALL LOSS VALUES OF RESNET-50 AND RESNET -101

| Epoch | ResNet-50 Loss Value | ResNet-101 Loss Value |
|-------|-------------------------|--------------------------|
| 1 | 0.7370 | 0.4272 |
| 5 | 0.0689 | 0.0418 |
| 10 | 0.0384 | 0.0277 |
| 15 | 0.0329 | 0.0256 |
| 20 | 0.0286 | 0.0218 |

An augmentation technique is applied to increase the number of image data, and the concept of transfer learning is extended to landslide detection, showing to work well with limited amount of labeled data.

The main objectives representing also the novelty of the present article are as follows.

- To perform object detection task on landslide photographs for achieving landslide detection with minimal dataset using a pre-trained Mask R-CNN model.
- To use a transfer learning approach for achieving good results with finite training samples.
- To collect freely available landslide photographs from distinct sources for the creation of a suitable dataset available for research.
- To investigate the transferability of the trained network to alternative imaging modalities.

As regards this latter point, further analysis will involve an exact testing process using other types of CNNs. Effectiveness of different types of backbone networks can be tested in a similar way by establishing the connection between source and targets for future overhead imagery detection tasks.

The above objectives will be fulfilled through the following activities.

- Augmenting training samples to increase the volume of the training data (set A and set B).
- Fine tuning with limited photographs.
- Investigating pre-trained learning model performance by using ResNet-50 and ResNet-101 as backbone neural networks.

The rest part of this article is organized as follows: Section II explains the algorithmic procedure for landslide detection. Section III provides details of the proposed method for landslide detection. Section IV presents the simulation results. Section V summarizes the work and section VI provides conclusion along with future directions.

II. ALGORITHMIC PROCEDURE

In this section, methodology adopted for landslide detection is explained, followed by a brief introduction to transfer learning and Mask-RCNN.

- Transfer learning*: The main aim of transfer learning [32] is to transfer knowledge from a substantial dataset (i.e., source domain) to a smaller dataset (i.e., objective domain) as shown in Fig. 1. In the proposed work, transfer

TABLE II
PRECISION, RECALL AND F1 SCORE FOR DATASET A (160 IMAGES)

| Model | Type | P | R | F1 score |
|------------|---------------|------|------|----------|
| ResNet 50 | Landslide | 1 | 0.87 | 0.93 |
| | Non-Landslide | 0.89 | 1 | 0.94 |
| ResNet 101 | Landslide | 1 | 0.93 | 0.97 |
| | Non-Landslide | 0.94 | 1 | 0.97 |

TABLE III
PRECISION, RECALL AND F1 SCORE FOR DATASET A (121 IMAGES)

| Model | Type | P | R | F1 Score |
|------------|---------------|------|------|----------|
| ResNet 50 | Landslide | 1 | 0.73 | 0.85 |
| | Non-Landslide | 0.8 | 1 | 0.89 |
| ResNet 101 | Landslide | 0.93 | 0.87 | 0.90 |
| | Non-Landslide | 0.88 | 0.94 | 0.91 |

TABLE IV
RANDOM FRAMES ACCURACY OUTPUT FOR RESNET-50

| Frame | Detection Accuracy (%) | Frame | Detection Accuracy (%) |
|-------|------------------------|-------|------------------------|
| 1 | 99 TN | 6 | 99 FN |
| 2 | 98 TN | 7 | 98 FN |
| 3 | 97 TP | 8 | 91 FN |
| 4 | 90 TP | 9 | 96 TP |
| 5 | 98 TN | 10 | 90 FN |

TABLE V
RANDOM FRAMES ACCURACY OUTPUT FOR RESNET-101

| Frame | Detection Accuracy (%) | Frame | Detection Accuracy (%) |
|-------|------------------------|-------|------------------------|
| 1 | 99 TN | 6 | 99 FN |
| 2 | 98 TN | 7 | 99 FN |
| 3 | 99 TP | 8 | 90 TP |
| 4 | 96 TP | 9 | 94 TP |
| 5 | 99 TN | 10 | 89 TP |

- learning is used since it allows to deal with a smaller number of landslide images.
- 2) Common Objects in Context (COCO) Dataset [33]: In this article, trained weights of COCO dataset are utilized for landslide detection model, and the last output layer only

TABLE VI
LOSS VALUES OBTAINED USING CV ($K = 5$) FOR RESNET 50

| ResNet-50 | Epoch 1 | Epoch 5 | Epoch 10 | Epoch 15 | Epoch 20 |
|-----------|---------|---------|----------|----------|----------|
| CV1 | 2.0080 | 1.2609 | 0.8921 | 0.7466 | 0.6044 |
| CV2 | 2.0514 | 1.2540 | 0.9142 | 0.8457 | 0.6247 |
| CV3 | 1.8483 | 1.2511 | 0.9051 | 0.8214 | 0.6156 |
| CV4 | 1.8440 | 1.2340 | 0.8766 | 0.7265 | 0.5969 |
| CV5 | 1.9273 | 1.1371 | 0.9139 | 0.7636 | 0.6195 |

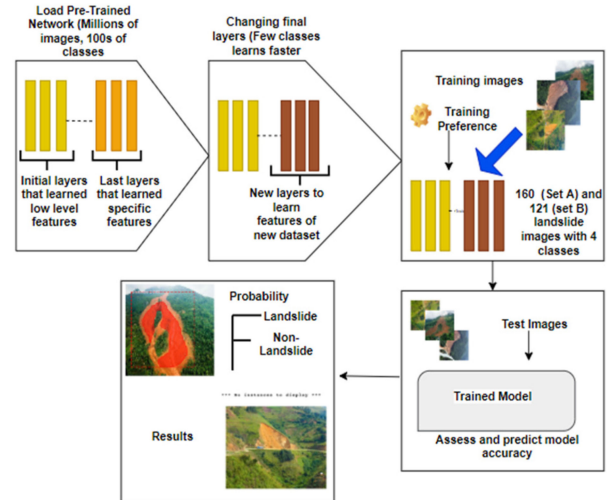


Fig. 1. Transfer learning for landslide detection.

is trained by using landslide labeled images. COCO pre-trained weights are used for both ResNet-50 and ResNet-101 CNNs.

- 3) ResNet: It is also known as residual network. It is a powerful framework in training a deep neural network. In our work, ResNet-50 and ResNet-101 are used. ResNet-50 is a deep residual network with 50 layers which is a subclass of the convolutional network and most popularly used model for image classification. Similarly, ResNet-101 is a CNN having 101 layers. In both CNNs (ResNet-50 and ResNet-101), bottleneck design has been used. There are five stages in ResNet architecture but in our work, we have used only 4 stages, since we are using transfer learning.
- 4) Mask R-CNN: It is an extension of Faster R-CNN pixel-level image segmentation [34]. Therefore, point is to decouple the pixel-level mask prediction task and the classification. Based on faster R-CNN framework, Mask R-CNN adds a third branch for prediction of object mask in parallel with current branches to perform localization and classification.

Faster R-CNN is capable of classifying the objects but unable to find which pixel belongs to an object in a particular image. Thus, Mask R-CNN is derived and used for instance segmentation as shown in Fig. 2. Further, instance segmentation is divided into two parts i.e., semantic segmentation (also referred as pixel

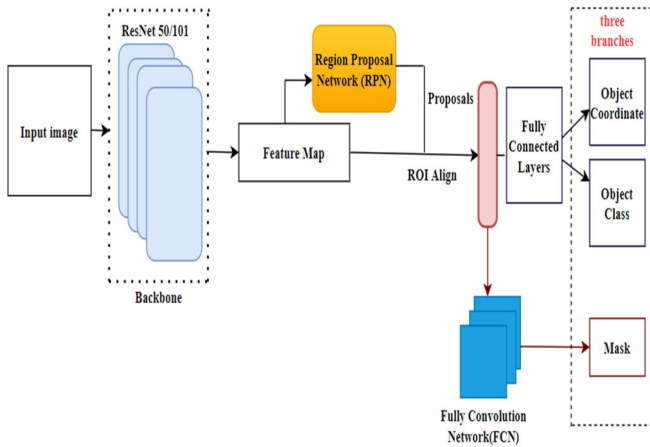


Fig. 2. Mask R-CNN overview.

level segmentation) and object detection. In Mask R-CNN architecture, fully connected network (FCN) and object detection are enforced on individual region of interest (ROI), which is used for semantic segmentation. The improved version of ROI pooling, i.e., ROI Align layer, is used with Mask R-CNN for providing pixel level segmentation in the images. In fact, in ROI pooling, misalignment of object location appears due to quantization. To avoid quantization and in order to build ROI pooling more precisely, Bilinear Interpolation is used, known as ROI Align.

For saving training resources and ensuring the model performance on landslide images, we fine-tune the Mask R-CNN model pre-trained with COCO dataset. Here, fine-tuning implies application of previously learned knowledge to new knowledge i.e., weight of each layer is initialized by utilizing the parameter layer of the trained model. The landslide feature extracted by the deep learning model is hierarchical in nature. The features extracted by lower-level networks are randomly combined and extracted by high level networks, providing common primary information in different datasets. In the proposed work, the initialization parameters are the parameters of the models, trained on the COCO dataset and then the model is fine-tuned with the new landslide image dataset. The size of the anchor box is 32, 64, 128, 256, 512 and the aspect ratio is 0.5, 1, 2 with learning rate 0.001 and a momentum of 0.9. The batch size is 2 with 1000 steps/epoch, total number of epochs are 20 with 50 validation steps.

It is worth to highlight that the Masked R-CNN method used for landslide detection in the presented work can have manifold applications in covering other wide domains, as shown in the further description. Boundary regularization for building extraction, by utilizing Mask R-CNN algorithm along with ResNet-101FPN, is for instance the backbone model in [35]. Zhao *et al.* suggested a precise Mask R-CNN based methodology for both instance segmentation and object detection in very high resolution (VHR) remote sensing images. Moreover, they used the COCO annotation format and compared the proposed methodology with the conventional Mask R-CNN model using the F1 score metric. The ResNet-101FPN and ResNet-50FPN backbone model in Mask R-CNN have been applied and the

new pooling technique implemented by introducing precise ROI pooling in NWPU VHR-10 dataset, containing few pan sharpened color infrared images and mostly RGB images. The proposed method was also evaluated on the COCO metrics i.e., AP, AP50, and AP75. Mahmoud *et al.* in [36] proposed adaptive Mask R-CNN for detection of multiple class objects present in remote sensing images. To overcome the scarce labeled remote sensing data, they utilized transfer learning approach, different augmentation techniques and fine-tuning, by out-performing other object detection methods. Maxwell *et al.* proposed a deep learning-based Mask R-CNN method to extract valley fill faces using elevation data obtained from LiDAR sensors in [37]. The proposed model performs well with LiDAR data when it is applied to other geographic locations, independent of acquisition mode and sensors. Improved Mask R-CNN was implemented by Nie *et al.*, for ship detection and segmentation by adding bottom-up structure and attention mechanism to the Mask R-CNN [38]. The proposed method of ship detection is capable of simultaneously segment and detect ships in a single framework using Airbus ship dataset. A unique building extraction framework known as “Mask R-CNN fusion sobel” is proposed by Zhang *et al.* using high resolution remote sensing images [39]. The proposed framework is based on CNN and edge detection algorithm achieving average value of intersection over union (IOU) 88.7 and kappa value 87.8.

A new Mask R-CNN model was implemented by [40] to calculate the building areas, by extracting the outline of each building using drone aerial images. The proposed method achieves good results in terms of IOU and F1 score. MASK R-CNN with ResNet-101FPN is applied in SAR imagery for oil spill detection using tensor flow and Keras in [41]. The authors analyze IOU, F1, recall, specificity, and accuracy showing encouraging results. In [42], Subash *et al.* implemented Mask-RCNN to classify, locate and detect distinct objects present in the images and videos acquired by a Ryze Tello drone, by achieving a better accuracy in detection.

III. PROPOSED METHOD OF LANDSLIDE DETECTION

In the article, we have explored on open source landslide photographs, acquired by UAVs, a landslide detection method using a Mask R-CNN as deep neural network, along with transfer learning for training the proposed model. The landslide detection framework consist of: data processing (for resizing and augmentation of the images); data labeling (for defining the classes i.e., landslide, vegetation, water body, building and background), and dataset creation (set A and B), as shown in the Fig. 3. The state-of-the-art for deep learning methods shows an encouraging set of technologies that fit the current requirement for analysis of high-resolution UAV images because of their superior capabilities for learning higher-level representations from raw images.

The proposed algorithm comprises of: backbone network; region proposal network; mask representation; and ROI Align layer. This ROI layer has been introduced as new layer for Mask R-CNN in [33] to solve misalignment problems.

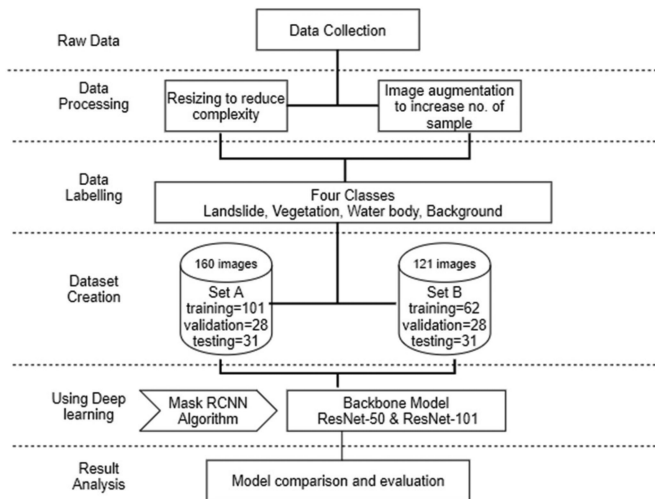


Fig. 3. Proposed landslide detection method based on Mask R-CNN and transfer learning.

In the proposed article, ResNet-the 50 and ResNet-101 are used as backbone networks for generating feature maps from landslide images. Feature maps generated from previous layers are passed through convolutional filter producing the variable size of anchor boxes containing various objects in the image. These anchor boxes are passed into parallel branches determining the objectness score of landslides and regress the bounding box coordinates. Then, a fully connected layer is used for mask prediction on landslide images, and in order to generate its input, a fully connected ROI Align is used for separating masked object from background image. The purpose of ROI Align is to convert the feature map with different sizes into a fixed-size feature map. A mask encompasses spatial information about the object, i.e., landslide in the input images.

- 1) *Data Collection*: In recent years, closed-range remotely sensed images obtained from UAV photogrammetry have shown intense growth in landslide studies [23]. UAV images are acquired without human supervision and presently essential for developing different military, civilian and disaster monitoring applications. The dataset used in this research work is composed by several images including high resolution digital photographs, mainly acquired by UAVs, and freely downloaded from the available search engines (i.e., Bing, Google) and other sources, through a Python script written to this purpose. Some specific images that belong to particular terrains having landslides, were manually selected by visual inspection to analyze those photos that appear to be most representative for the landslide detection in the hilly region, as shown in the Fig. 4. The unique challenge with UAV images and web-based photographs for landslide studies is non-standard and non-nadiral [43].
- 2) *Data Processing*: A significant contribution in this article is the creation of a landslide image database and preprocessing of training data, since there is no photograph-based landslide imagery database available. Therefore, all downloaded landslide images are classified and assessed



Fig. 4. Sample photographs with and without landslides.

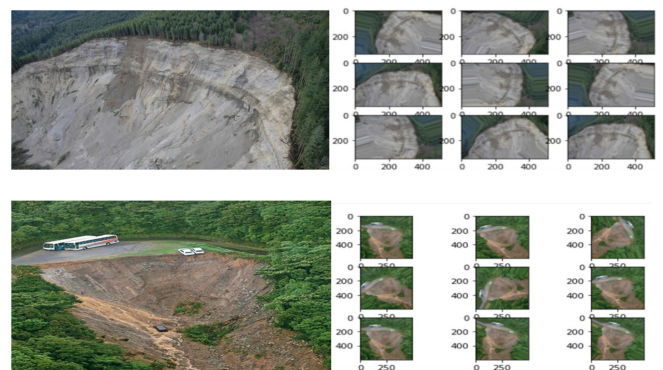


Fig. 5. Augmented outputs of sample images.

manually. After the selection of the images, two preprocessing steps are applied: resizing the image to reduce the complexity: resized images have a size of 512*512 pixels; and (ii) image augmentation applied by using the Image data generator (from the Python library) for increasing the number of training images, and improving the training suitability for the deep learning algorithm, as represented in the Fig. 5.

- 3) *Data Labeling and Annotation*: Data labeling is done to prepare the dataset for training the deep learning algorithm. Labeled data contain meaningful tags that are informative. In this article, five classes have been defined, namely landslide, vegetation, water body, buildings, and background, as shown in the Fig. 6. For data annotation, the “VGG Image Annotator (VIA)” is used to define regions in an image and to add textual descriptions of these regions. VIA is an open-source project, based on HTML, CSS, and JavaScript, and developed at the visual geometry group (VGG) [44], [45]. Further, the developed landslide image database along with programming codes have been published on GitHub platform [46] for reproducible research to be carried out by the interested research groups.
- 4) *Dataset Creation*: Dataset is divided into three folders: training; testing; and validation. Training data are part of the data, which help the deep learning model to make predictions. Validation data help to know whether the



Fig. 6. Image annotation using the VIA developed by the VGG.

model is capable of correctly identifying the new examples or not, and also, they include images, used by the model to check and keep track of its learning. Testing folder contains images from which the model accuracy can be predicted. Two datasets are created set A (training = 101, validation = 28, testing = 31) and set B (training = 62, validation = 28, testing = 31). The purpose of creating two data sets of different sizes, is to observe the performance consistency of the proposed landslide detection model.

- 5) *Mask R-CNN for Landslide Detection*: Mask R-CNN algorithm proposed in this article, and its implementation, operates through an open-source library, to perform various tasks (TensorFlow, in this case). All experimental works are conducted on Google Colaboratory (Google Colab). Colab notebooks are capable of executing code on Google's cloud servers. Moreover, Microsoft (MS) COCO pretrained weights for ResNet-50, and ResNet-101 models are used. As underlined before, 4 classes are used for the considered images, although MS COCO dataset makes available 80 different classes. In the Fig. 7. the Mask R-CNN scheme is shown.

In the proposed Mask R-CNN model, digital photographs from the created data sets are annotated and the file (.json extension) containing the coordinates of the defined classes is generated. The considered transfer learning backbone model will be trained using this file. Weights of head layers are generated, and when the testing images are passed through the considered ResNet model, the different regions are separated using a regional proposal network (RPN), helping to produce high-quality regions. In this way, different feature maps are generated corresponding to different regions.

The proposed new Mask R-CNN algorithm is composed of two parts: First, the ResNet-50/101 convolutional backbone architecture to extract features from an entire image. Second, network head used for bounding box perception, classification along with mask prediction, individually applied to each ROI (region of interest). In the Fig. 7, input image is passed through

convolutional backbone network i.e., ResNet-50 and 101. The output of first convolutional network is downsampled, pixel value of which is further pass through the region proposal network, that creates distinct anchor boxes (ROIs), depending on the existence of the objects to be detected (in our case landslide). In the next stage, anchor boxes are processed by ROI Align to protect the spatial orientation by using bilinear interpolation. The main purpose of ROI Align is to make all ROIs of same size for further processing. The output obtained from previous layer is sent to the fully connected layers to generate the object class as a result for specific region along with bounding box, representing the location of object. In the last step the output obtained from ROI Align is fed to convolutional layers parallelly, intended to generate a mask of the object.

ROI Align unit is used and a fixed size feature map is generated, which will be used for detecting the landslide regions on the image. Accuracy of the formed regions is determined by the trained transfer learning model.

The fixed size feature map or intermediate activations are convolved over the image and the corresponding objectness scores are generated, as shown in Fig. 8.

Bilinear interpolation is utilized by ROI Align, for creating feature maps with fixed dimension (for example 7×7). The main purpose of fixed size feature map is to make a pool of all ROIs having fixed size. The position of ROIs is obtained from RPN, having floating point number. To make all ROIs of fixed size, ROI align is adopted to avoid the quantization errors. These scores are indicative of the target object presence in the image under consideration, which vary between 0 to 1. Visualization of feature map helps to understand the way in which input landslide image is transferred through various convolutional layers, as also depicted in Fig. 8.

Fully connected layers, using a particular objectness score threshold value, classify the image into two classes i.e., landslide and nonlandslide (i.e., binary classification). Generally, a threshold of 0.8 is used in this case and a gradient descent optimization algorithm is applied to update the training parameters such as the learning rate. Learning rate for our proposed Mask R-CNN model has been set to 0.001. Furthermore, the number of the epochs has been optimized by considering the obtained loss error values.

IV. SIMULATION RESULTS

In Table I the overall loss value generated after each epoch is given for ResNet-50 and 101.

We have observed that the overall loss reduces while landslide detection accuracy increases for both the ResNets. Yet, it has been also observed that overtraining does not produce benefits since it increases the loss and reduces the accuracy.

In this section, some definitions are introduced, necessary for the comprehension of the runned simulations and performance evaluation of the proposed method.

- 1) *Accuracy Assessment*: Effectiveness and performance of the proposed landslide detection algorithm are evaluated using three quantitative parameters, i.e., precision, recall and F1 scores.

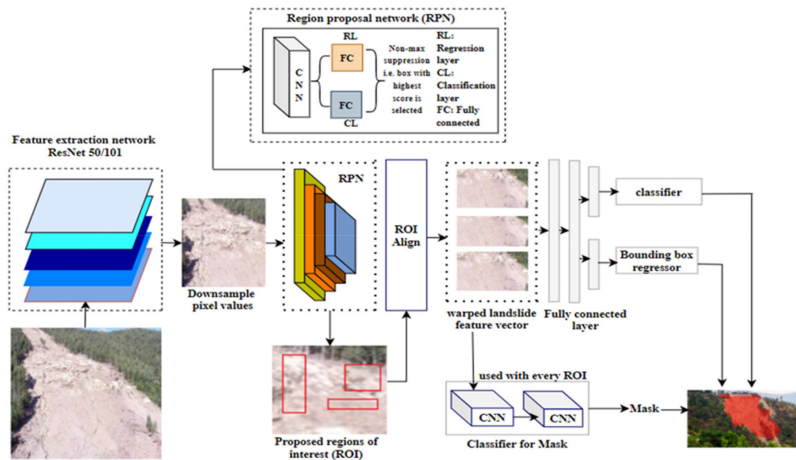


Fig. 7. Mask R-CNN network for landslide detection.

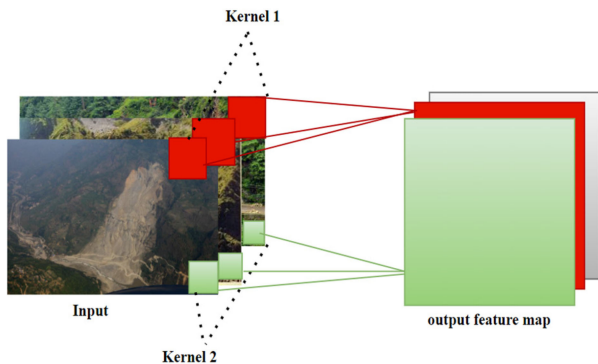


Fig. 8. Illustration of feature map.

The Precision measure is used for finding the correctness of landslide area detection.

The Recall measure is used for defining how much of the actual landslide regions were identified in the image. The balance between Precision and Recall measure is calculated by using the F1 score.

The above measures can be calculated using the following equations:

$$\text{Precision } (P) = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall } (R) = \frac{TP}{TP + FN} \quad (2)$$

$$F1 \text{ score} = 2 * \frac{P * R}{P + R} \quad (3)$$

where TP stays for true positive, and it represents the landslide area accurately described by the applied methodology. FP stays for false positive, and it is defined as nonlandslide regions detected by the applied methodology as a landslide region in the image, whereas FN stays for false negative and it shows actual landslide regions that are not detected by the applied methodology.

The precision, recall and F1 scores calculated for dataset A and dataset B are shown in Tables II and III.

 TABLE VII
 LOSS VALUES OBTAINED USING CV ($K = 5$) FOR RESNET 101

| ResNet-101 | Epoch 1 | Epoch 5 | Epoch 10 | Epoch 15 | Epoch 20 |
|------------|---------|---------|----------|----------|----------|
| CV1 | 1.9537 | 1.1310 | 0.7226 | 0.6214 | 0.5269 |
| CV2 | 1.8421 | 1.1620 | 0.8425 | 0.6408 | 0.5079 |
| CV3 | 1.8433 | 1.1216 | 0.7775 | 0.6546 | 0.5597 |
| CV4 | 1.8173 | 1.0116 | 0.7909 | 0.7234 | 0.4737 |
| CV5 | 1.5990 | 1.0287 | 0.6791 | 0.6213 | 0.4347 |

- 2) *Frames Accuracy*: Mask R-CNN with its constitutive parts, i.e., faster R-CNN and RPN, is used to check objectness score and detection accuracy. The proposed object detection model is tested on landslide images, and overall accuracy of the model can be observed from Tables IV and V. Rectangular bounding boxes are generated along with the frame if the accuracy of the detected object is above 80%. Generally, accuracy will range between 95%–100%. Accuracy, the percentage of correctly predicted data out of all the data, can be calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

where, TP, FP, and FN are as above defined, and TN stays for true negative, and it represents the nonlandslide area accurately described by the applied methodology.

- 3) *k-fold Cross Validation*: k-fold cross validation (CV) is a statistical approach based on resampling procedure for estimating the performance of the deep learning model on the limited dataset. In the proposed work, dataset is divided into training and testing data. The five-fold CVs are calculated for both backbone models (i.e., ResNet-50/101), demonstrating the loss value obtained as given in Tables VI and VII. It is observed from the tables that the loss value decreases with the increase in the number of epochs. Further, the average loss values for the considered

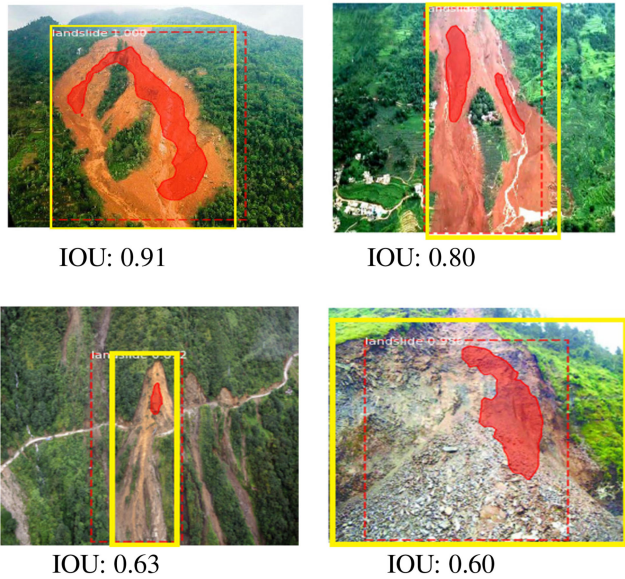


Fig. 9. Landslide detections from ResNet-50.

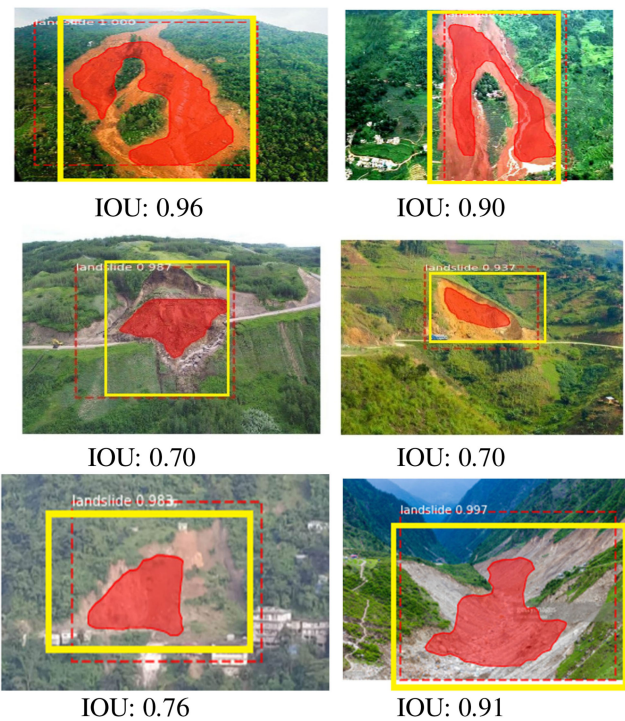


Fig. 10. Landslide detections from ResNet-101.

backbone models are found to 0.61 (ResNet50) and 0.50 (ResNet101) respectively.

- 4) *Bounding Boxes as Detected Results:* The Mask R-CNN algorithm utilizes a FCN for mask prediction in the output image. Mask generated around the target object contains spatial information about the object as shown in Figs. 9 and 10. While comparing, it is found that instance segmentation is more beneficial with respect to semantic segmentation, for differentiating between samples having the same classes. It generates a colored mask in sample images to

represent different objects with different colors, and due to this reason, it is mostly preferred for object detection tasks. As compared to Mask R-CNN, faster R-CNN takes least inference time and uses region proposal network to predict the region proposals. The predicted region proposals are re-shaped by using ROI pooling layer, which is also used to classify the image within the proposed region and even predicting the offset values for the bounding boxes.

Some more potential landslide images of Hindu pilgrim sites located in the Himalayan region of India (Kedarnath and Badrinath) have been added in the reference dataset, recently made available on Git-Hub [46].

Figs. 9 and 10 also show the landslide detection results, of the proposed Mask R-CNN method, on some of these new images.

From the Tables II and III, it is found that correctly predicted positive observation for landslides is 1 with ResNet-50 for both datasets A and B. While using ResNet-101 correct prediction for the landslide is 1 with dataset A, and 0.93 with dataset B. It is also observed that in ResNet-50 model with dataset A, out of all positive samples, 0.87 landslide samples are picked by the model. Whereas with dataset B correctly chosen samples are 0.73. In the case of ResNet-101, correct landslide samples taken by the model corresponds to 0.93 with dataset A and 0.87 with dataset B. Furthermore, it is observed that landslide classification accuracy is 0.93 when dataset A is used whereas classification accuracy reaches 0.85 when dataset B is used with ResNet-50. When ResNet-101 is used, classification accuracy reaches 0.97 using dataset A, and it reaches 0.9 with dataset B.

V. DISCUSSION

Landslide detection by using deep learning frameworks requires a large number of datasets with high resolution, for building the models. Developing a deep learning-based model for landslide detection may be a significantly complex task. In this article, a pretrained framework, a Mask R-CNN is used to extract landslides of a specific terrain. Transfer learning by using pretrained deep learning frameworks has been also exploited, by showing a promising approach for improving the object detection performance in deep neural networks. In the proposed research work, the Google Colab has been used for training and, two preconfigured neural networks, i.e., ResNet-50 and 101, have been used as backbone models and for the accuracy assessment of the proposed method. Evaluation was done by using three metrics, i.e., precision, recall and F1 measure. Two different datasets were created: set A (160 images) and set B (121 images), for training and testing. To improve the results, an image data generator was applied to artificially expand the size of the training dataset by creating modified versions of the images present in the dataset. Model training was performed by using COCO dataset, and trained weights were utilized for landslide detection, and the output layer (head of the model) was trained by using landslide labeled images. In the process of landslide detection using the proposed methodology, 20 epochs were completed, with unitary batch size.

We could observe that as the number of epochs increased, more number of times the weight has changed in the neural

TABLE VIII
COMPARATIVE ANALYSIS OF THE PROPOSED ARTICLE WITH A FEW WORKS
FOUND IN LITERATURE

| Research Work | Method | Performance | Classification Metrics |
|-----------------------------|--|--|--|
| [36] | 1. Evaluation of number of ML Methods 2. Applied to certain area of testing | 1. Generalized and average performance | Precision: less than 1.00 Recall: 0.92 F1 Measure: 0.87 Values not obtained for all methods |
| [37] | 1. Deep learning & Transfer learning 2. Tested for specific plants & Geography | 1. Improved automation of landslide acquisition | Confusion matrix (Yet, evaluation of detection and classification by other measures are missing) |
| New Mask R-CNN Based Method | 1. Mask-RCNN, a hybrid framework 2. Tested for both Italy and India geographic contexts | 1. Addressed with help of many metrics as shown from Table I to Table III 2. Highlighted evaluation and detection as well as classification 3. Improved detection of landslide also achieved | Precision: 1.00 Recall:0.93 F1 measure: 0.97 Better Robustness |

network and the cost function curve goes from under-fitting to optimal and then to overfitting curve. Five object classes were used, i.e., landslide, vegetation, waterbody, and background. Simulation results revealed that high F1 scores have been reached. The total number of 31 landslides were detected from ResNet-101 using 160 images with the highest 1.00 precision, 0.93 recall and 0.97 F1 scores. From the above results, it is concluded that the proposed methodology can be used for distributed landslide detection, but at the same time, it is still a challenging task to get sufficient amount of training samples with high resolution. Further, we are planning to use an object classification method instead of object detection to improve the accuracy of landslide detection.

In Table VIII, we have compared the performance of the proposed method with few important and relevant works existing in the literature [47], [48]. It is worth to underline that we could find only one work which was attempting to use transfer learning in combination with deep learning for landslide detection [48]. Other comparisons have been done with [47], a review paper which has analyzed the performance of many ML-based methods applied to landslide detection.

While in [47] the study was subjected to some selected areas, the proposed method covers landslide studies and cases of different regions, and it is applicable both to India and Italy in larger perspective (and in general to other different countries). In the other work [47], landslide detection was specifically implemented using deep learning and transfer learning. However, the Confusion matrix has been only used as performance measure and the evaluation was performed for acquisition only. In the proposed work, we have instead assessed the performance of detection as well as classification with the help of necessary measures and metrics. Moreover, our method has used robust measures for larger geographical contexts. Thus, we consider that the proposed method has outperformed the existing noteworthy research.

In the proposed article landslides in hilly areas were considered. The external triggering factor of these types of landslides includes earthquakes and heavy rainfall. Excess rainfall

increases pore water pressure resulting in slope slips capable of travelling at high speed, also known as a debris flow. A large number of landslide images were gathered from different web resources, and some specific images that belong to particular terrain having debris flow were manually selected by visual inspection.

On the other hand, entirely irrelevant images, like flooding photographs and images with extreme small sizes were discarded while preparing training datasets. The current supervised approaches have hardly considered the generalization issue [49], i.e., a model learns from one dataset and is appropriately transferred to a new dataset. Specifically, when dealing with limited training samples, the pretrained models can only be used for object detection tasks. Hence, the main issue is utilizing the learned knowledge of the well-trained model (trained on a large dataset) to explicit regions having limited training samples along with the target to improve the fitness of the model. Therefore, to generalize the proposed model on another limited dataset, data augmentation is utilized to resolve the overfitting problem. For each image a horizontal flip is performed using Image data generator class.

VI. CONCLUSION

Since the issue of analyzing pictures of landslides can be relevant for cultural heritage [49], this article proposed an image-based landslide detection method by combining a pretrained Mask R-CNN model with transfer learning. Particular historical sites were selected, and a deep neural network, i.e., a Mask R-CNN, was used to test the performance of the model on landslide images. After getting the results, it is concluded that ResNet-101 performs better than ResNet-50, with 1.00 precision, 0.93 recall and 0.97 F1 measures, with a total number of 31 landslide detections on dataset A. Also, landslide datasets used in the article provide unique data references for a similar type of research. Moreover, the proposed method has outperformed the existing relevant research both in terms of performance measures and robustness. The main problem that we have faced is the annotation of training images which is a very time-consuming task. An object classification methodology instead of the object detection would be attempted in future to improve the accuracy for the landslide detection while resolving the manual annotation of images. This will allow the proposed model to be trained for multiple types of terrains, which is not based on masked instances. Further study also includes improvement in traversal scheme so that, loss value will be monitored.

The novelty of this article is the application to digital photographs of target hilly areas, acquired by UAVs, of Mask R-CNN and the performance demonstration as well as its effectiveness in landslide detection is tested with backbone models i.e., ResNet-50/101. The aspect of the detection in this article is bounding box, class label (i.e., landslide) with prediction confidence and mask is obtained. The main advantage of using Mask R-CNN algorithm is the ability to perform both instance segmentation and detection of landslides within the images allowing further improvement in the algorithm to perform analysis of other natural hazards.

Challenges while using UAV images with proposed algorithm represent further analysis and future work. In fact, UAV images are acquired without human supervision and presently essential for developing different military, civilian and disaster monitoring applications. However, UAV interface has flight persistence limitations which restrict weight, size and payload power consumption. In the field of natural hazard monitoring like landslides, the critical task dedicated to UAV systems is a brief survey of large areas that are too large for physical investigation and require detailed scale analysis. Due to limited battery life, it isn't easy to cover a large extent (Ghorbanzadeh *et al.*, [48]). The unique challenge with UAV images and web-based photographs for landslide studies is non-standard and non-nadiral (Minaeian *et al.* 2016, [43]). The advantage of using UAV images is the ability to operate quickly and gather historical, monitoring and mapping data (Catani, [23]). The state-of-the-art for deep learning methods has an encouraging set of technologies that fit the current requirement for analysis of high-resolution UAV images because of its superior capabilities for learning higher-level representations from raw images.

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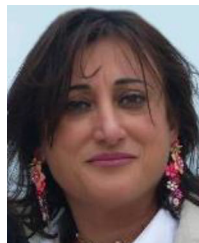
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