Landslide Detection From Natural Disasters Through Deep Learning

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ABSTRACT

Accurate landslide detection is useful for planning and managing post-disaster reconstructions. By using the deep-learning-based approach, we can detect the landslide after a natural disaster by using satellite imagery. Currently, visual interpretation is still the most widely adopted technique for landslides mapping, which is time-consuming and costly. In the existing system, hazard and risk mapping are used to know whether the area is a hazard-prone area or not by analyzing the risks from targeted studies from previous years. To know about risk analysis, we have to analyse the occurrences of landslides, places of landslides, and the impact of dangerous events to map to the current and give predictions of the future. The proposed system collects data from satellite imagery. After collecting data, it classifies the data as sliding and not sliding for training. Then the authors do training and test the model. Later they check the effectiveness of the model.

I. INTRODUCTION

A landslide is described as a collection of rocks, rubble, or soils that move down a slope due to gravitational pull. A rapid failure of a slope within these regions where humanity has an impact can cause an enormous loss of money and human life. Approximately 3.7 million km2 of land has been marked by The World Bank as prone to landslide with 820,000 km2 classified as high-risk zones (Aghdam et

DOI: 10.4018/407413

al., 2016). This problem adversely affects around 300 million people or about 5 percent of the global population. From 2005 to 2016 approximately 55,997 people lost their lives to non-seismic landslides. Additionally, there is danger posed to technical infrastructures such as roads, buildings, and dams due to the active rotational slumps of weak slopes. Sometimes this instability can result in a catastrophic landslide that moves rapidly and affects whole slopes or parts of slopes, often due to external forces such as intense rainfall, earthquakes, volcanic activity, or even humans (Aslam et al., 2021). Due to the destructive impact of landslides on human life, research on natural hazards has moved towards prioritizing the study of landslides. A lot of research has already been conducted regarding the processes involved in mass-wasting, with the goal to understand its relationship with conditioning factors, identify hazard areas and estimate the associated risk (Azarafza et al., 2021). Each time a landslide occurs, there is a change in the geomorphology of the region and its accompanying area which results in the formation of unique surface morphological features which can appropriately represent the slopes failing due to landslides. The essential prerequisite to effective hazard evaluation, risk mitigation, and disaster response are maps showing the spatial distribution of antecedent landslides and sites of current slope failures. It has been common practice to map landslides by simply recording geomorphological features in the field from the very beginning (Banerjee et al., 2025). Mapping surface features involves a lot of fieldwork and depending on the size or location of the phenomenon, viewing it in its entirety may not be possible. After a serious catastrophic failure, there are often planned aircraft surveys to collect pictures for stereoscopic aerial photograph interpretation to facilitate the field mapping activities. The prior condition of the ground surface is not revealed, only a synoptic picture of big landslides.

Today, there is a sizable network of satellites in orbit that routinely collects and stores high spatial resolution Earth Observation (EO) photos (Chen et al., 2017). The most popular technique for creating landslide inventories at the moment is visual and semi-automated interpretation of optical satellite imagery with proper field validation. It is now possible to retrieve historical satellite photographs for comparison purposes or to track the development of an unstable slope. The physical characteristics connected to landslides may be found using high-resolution Digital Elevation Models (DEMs). But since the majority of these visible characteristic markers are post-failure deformation surface features, they don't tell us anything about how things are going right now. The extent of the region of interest and the amount of data available will determine the constraints of any interpretations made using remotely sensed data. These interpretations will also require a lot of human interaction and subjectivity (Cheng et al., 2021). Less than 1% of the total slopes on the land surface have a systematic landslide inventory, which is mostly due to this. Regional landslide catalogues have historically been mapped; however, they are frequently not updated. Due to the next satellite deployments, it is anticipated that the repository of current EO data will continue to grow tremendously in size. As a result, it is anticipated that EO data availability will expand at a rate of tens of petabytes per year or more (Feizizadeh & Ghorbanzadeh, 2017). With this much data, it is becoming increasingly challenging, if not impossible, to evaluate all of the scenes using human or semi-automated techniques. As a result, the bulk of captured photographs are stored in archives until they are retrieved for certain investigations. Every subject has seen a significant increase in the use of machine learning, which is complemented by an increase in digital data and an improvement in computer infrastructure. Machine learning has been quickly embraced by the geoscience community for a variety of uses (Feizizadeh et al., 2014). A project is now underway to create an automated system for mapping landslides. With the presumption that landslides are more likely to occur under circumstances similar to those that have caused the prior disasters, the majority of the work done so far favours supervised learning techniques. In order to automatically identify landslides in places that have not yet been

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