Landslide Disaster Management using Satellite Imagery

Sandeep Babu. S[1], Sri Krishna. V[2], Yashwanth. S[3] and Jayasakthi[4]
{21ec71@kcgcollege.com[1], 21ec84@kcgcollege.com[2], 21ec93@kcgcollege.com[3]}

Department of Electronics and Communication Engineering, KCG College Engineering (of affiliation), Karapakkam, Chennai -600097, Tamil Nadu, India[1, 2, 3]
Professor, Department of Electronics and Communication Engineering, KCG College of Technology (of affiliation), Karapakkam, Chennai -600097, Tamil Nadu, India[4]

Abstract. Mass movements are one of the most severe and frequent natural disasters that pose severe hazards to human life, property as well as environmental resources. Effective disaster management can also help reduce the impacts. In this paper we introduced to managing the landslide disaster from satellite imagery all at once system. The methodology presented combines advanced remote sensing, machine learning and geographic information system (GIS) methods for better landslide prediction, monitoring and response. Remote sensing satellite data are used to determine landslide susceptible areas using (i) terrain analysis, (ii) vegetation cover, and (iii) soil moisture determination. Such models based on machine learning classifier, have been developed using historical landslide information and satellite-derived variables to predict the susceptibility with great accuracy. In addition, live satellite data allows the active landslide zones to be monitored on a 24/7 basis and can thus be utilized in early warning and evacuation processes. After the disaster, satellite images can be used to assess the damage and plan recovery based on detailed spatial information. The identification of landslide-prone areas demonstrates the potential of satellite imagery in enhancing disaster risk reduction strategies. The study highlights the vital importance of satellite imagery in landslide disaster management, providing a scalable and low-cost solution for communities worldwide that are susceptible to such disasters.

Keywords: Landslide, disaster management, satellite imagery, remote sensing, machine learning, GIS, early warning systems, damage assessment.

1 Introduction

Triggered due to various factors such as intense monsoon rainfall, seismic activities and anthropogenic ones like the above ground excavations, land use change, landslides are emerging as increasing hazard to the human society especially in the mountainous and hilly regions. Risk reduction measures are effective in decreasing these risks; countermeasure mainly depend on good practice and emergency system. Remote sensing technology has developed rapidly recently, which makes it particularly useful for landslide monitoring, prediction and response.

One of the primary advantages of satellite imagery is its capacity to provide instant, high-resolution coverage over large areas in breaking situations. For the continuous surveillance of slide-prone areas, it has better performance compared to classical ground deformation methodologies which lack good spatio-temporal resolution and may be not applicable frequently or in remote terrain because of their cost (on site measurements) and access (field campaign)

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constraints. Even simultaneous combination of SAR + Optical + multispectral images improved the detection of precursors, susceptibility to landslides & post disaster monitoring too.

Recent studies have showed the successful application of satellite imagery in different stages of landslide disaster management. In the pre-impact phase, the satellite observation is used in hazard mapping and vulnerability analysis evaluating the topography and the vegetation cover and the soil moisture. In the disaster recovery phase, near real-time satellite imagery is useful for a quick assessment of the extent of the damage caused and for planning of emergency response. In the subsequent phase, it facilitates recovery and reconstruction efforts by offering detailed understanding on the level of damage and land use modifications.

However, several issues hindering the full potential of the satellite images being used for landslide disaster management still exist. difficulties such as good data resolution, processing speed and multisource information fusion still need to be enhanced or improved. Furthermore, the development of machine learning algorithms and artificial intelligence technologies, as well as their applications for analyzing big data from remote sensing satellites in Earth observation is also promising for automated landslide detection and prediction with high accuracy and efficiency. The aim of this paper is to describe the contributions made by satellite-derived image data to landsilde disaster management in detail, with a focus on new technological development, methodologies and case studies.

It also includes some of the recently developed technologies that include AI and cloud computing applied in construction of satellite-based landslide monitoring. Next, this study targets to provide insights for an evolving theoretical framework of landslide disaster management process which will be beter prepared and adaptive in order to minimize the social and economic costs on society and environment that killing nature like landslides with supports from further research by (both theoretically and empirically).

Landslides, an important natural hazard, are becoming more frequent and of greater consequence because of processes like climate change and urban expansion. Conventional detection and monitoring of landslide such as ground survey has limited spatial coverage, monitoring and real-time characteristic. Remote sensing methods, such as satellite imagery have proven to be a possible method for landslide detection and analysis.

The applications of Remote sensing and computer were worked properly in devising automatics systems for landslide detection and monitoring, which are useful for high-hazard assessment and Early-warning systems. Fossi and Lonkeng (2015) [1] show that remote sensing has been a useful method in studying the spatial and temporal variation of landslides vulnerable areas in resource-limited areas. Complementing this, Sreelakshmi et al. (2022) [2] presents the application of machine learning algorithms lits limitations, challenges and future work focusing on their ability to process massive datasets for trustworthy landslide detection.

At an applicative level, this document (Nardini et al. (2024) [3] also demonstrate the potential of combined SAR with optical data products to large-scale landslide detection and accentuate the superiority of multi-sensor application in complex area. Hanif and Ikhwanushova, 2017) [4] have likewise carried out the GIS and AHP analysis on landslide risk zoning which provides a networked operations research decision-making structure for regional planning.

So far as fast event response is concerned, Prakash et al. (2025).[5] Suggest the use of advanced leaning approach that used satellite SAR imagery in near-real-time to map and monitor landslides considering disaster management. Additionally, Tyagi et al. (2022).[5] provide a comprehensive overview for both the spatial and temporal as well as magnitude prediction methods, describing what has been achieved to-date and future challenges when dealing with landslide hazard predictions. Summarizing, all this evidence is a clear hint in the direction of combining remote sensing, GIS and machine learning methods to enhance predictive performances but also operating effectiveness of landslide monitoring as well as risk management.

2 Methodology

Theoretical Structure: It is a multistage process of handling landslide that involves processing of satellite image, subsequently with deep learning, and finally real-time monitoring such as identification and classification of the landslide. Here's a detailed explanation of the methodology:

Data Collection and Preprocessing: The project starts by getting the satellite images from available public datasets for landslide areas and also to areas that were not affected by landslides. These images are processed by resizing to 128x128 pixels for size consistency, normalizing pixel values between 0-1 for preventing saturation of the computation vector and also data augmentation techniques such as rotation, zooming, flip, and brightness to better dataset diversity and such that the model can generalize well. The Fig 1. shows Example satellite images from the dataset: landslide-affected areas (left) and non-landslide areas (right).

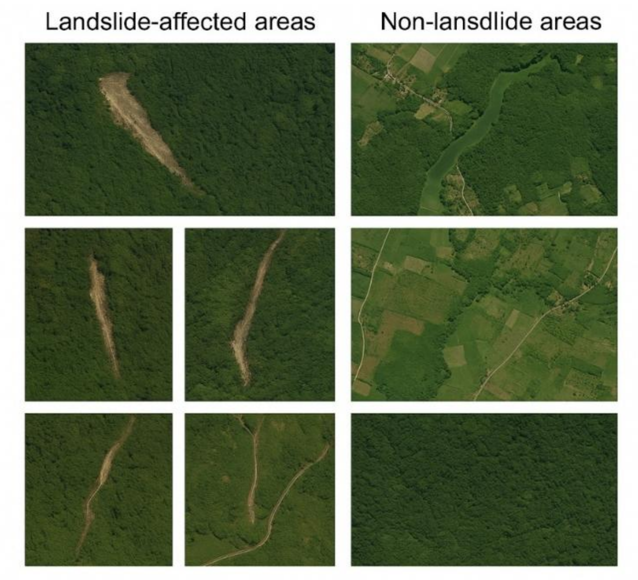

Fig. 1. Example satellite images from the dataset: landslide-affected areas (left) and non-landslide areas (right).

Model Development: For the classification problem, a CNN is used to extract features from satellite images and differentiate between "Landslide" or "Non-Landslide." It includes convolutional layers to extract features, pooling layers to reduce dimensions, and fully connected layers to classify. There is a sigmoid activation function in the output layer, and the model is compiled with Adam optimizer and binary cross-entropy loss function

Perceived source: The National Aeronautics and Space Administration (NASA) Earth Data, accessible through the NASA Earth Science Data Systems (ESDS) program, plays a vital role in landslide disaster management by providing high-resolution satellite imagery and geospatial datasets. Leveraging platforms such as the NASA Earth Observing System Data and Information System (EOSDIS), researchers can access multispectral and synthetic aperture radar (SAR) data, enabling the identification of land slide prone areas through terrain analysis, vegetation cover assessment, and soil moisture monitoring. The integration of NASA Earth Data with Geographic Information Systems (GIS) and Machine learning algorithms facilitates real-time landslide detection, early warning systems, and post disaster damage assessment. This data-driven approach enhances decision-making processes for disaster mitigation, response, and recovery, underscoring the significance of satellite based remote sensing in advancing landslide disaster management strategies.

2.1 Model software

Matplotlib: Matplotlib, a versatile and widely-used python library. For data visualization, serves as a critical tool in landslide disaster management by enabling the generation of high-quality output images from satellite imagery data. In the context of landslide analysis, Matplotlib facilitates the visualization of geospatial datasets, such as terrain elevation models, rainfall patterns, and soil moisture maps, derived from satellite sources like NASA Earth Data or Sentinel-1/2. By creating 2D and 3D plots, heat maps, and contour maps, Matplotlib aids researchers in identifying landslide susceptibility zones, monitoring temporal changes, and communicating findings effectively. Its seamless integration with scientific computing libraries such as NumPy, Pandas, and GDAL enhances its utility for processing and visualizing large-scale satellite datasets. The ability to export output images in various formats (e.g., PNG, PDF, SVG) ensures compatibility with reports and decision-support systems, making matplotlib an indispensable tool for advancing landslide disaster management through satellite imagery analysis.

AWS (SNS): In our Landslide Disaster Management, AWS SNS was utilized to send real-time alerts when landslide detected. An independent SNS topic (landslide alerts) was set up in the AWS Console, and members (e.g., local emergency responders) were added to be notified over email and SMS. But with our Python code, in the context of an SNS-alert-driven model, we were able to automatically cause the Boto3 AWS SDK to trigger an SNS alert every time the model detected a landslide from satellite images! IAM permissions were setup to enable SNS publishing, and the AWS CLI was used to test messages and observe their delivery. Linking provided immediate alerts resulting in improved speed of disaster response.

Monitoring in real time: Monitoring of the management of landslide disaster in real time using satellite data has become an important tool to reduce the disastrous effects faced by such a natural event. With the help of advanced remote sensing technologies, including Synthetic Aperture Radar (SAR) and optical sensors, ground deformation or soil moisture changes will be picked up as precursory signals of landslides in a high temporal resolution and spatial scale. The author raised the need to combine mechanisms that can recognize dynamic factors and methods that can process data in real time with landslide prediction in order to distinguish from the onset of precipitation events between occurring on a larger or smaller scale.

Furthermore, the satellite scrutiny could be continuously monitored over broad-remote zones which are difficult to access terrain and health decisions makers' perception results advantageously. This approach will improve the accuracy of landslide forecasting and be a reliable support decision tool for post disaster assessment and recovery work, which can minimize loss both human and economics. The IEEE is a beacon in the advancement of these technologies and fosters interdisciplinary collaboration that has great potential to enhancing the resiliency of landslide-prone areas.

3 Problem Statement

Landslides are among the most catastrophic natural hazards for human, structures and environment, particularly in mountainous regions and hillslopes. Rainfall intensity, seismic activity and human activities such as deforestation or inadequate management of the land are among the most common causes that trigger landslides. The impact caused by these phenomena is growing in greater intensity, flooding has become more frequent flooding, and many times, especially due to climate change and urbanization occident leads them to be a natura catastrophe. Conventional landslide detection, monitoring and risk low assessment regimens (for example field surveys and ground-based sensors) are limited in their spatial range, expensive and cannot provide immediate nor extensive data. These constraints are obstacles to efficient disaster management processes such as response, early warning system and post-disaster recovery.

To overcome these challenges, satellite remote sensing has become an available solution which provides wide area coverage, high spatial resolution and access to remote areas. But currently the application of satellite imagery for landslide disaster management has been affected by some technical and operational problems. These challenges are associated with advanced pre-processing of data and challenges related to noise in data and cloud cover, combination of multi-source satellite data (optical, SAR, LiDAR) and the development of machine learning models that are effective in predicting and mapping landslides. Moreover, the absence of standardized protocols for merging satellite data with GIS and field data restricts the utility and efficacy of satellite-based methods.

This paper attempts to fill up these gaps by establishing a full framework for the disaster management of landslides through satellite imageries. The research will concentrate on improving forward-looking, real-time and risk assessment capabilities for landslide early warning using state-of-the-art remote sensing, machine learning average and GIS. By addressing complexities in satellite imagery and in operations of the landslide, this research aims to develop a scalable and affordable method for the landslide early warning system to help improve landslide disaster management and to mitigate human and economic losses due to landslides.

Evaluation: The performance of the model is evaluated based on the validation dataset according to accuracy and loss. The training history is plotted to check how the model is learning (and decide if the model has learnt to distinguish a landslide and reduce the errors) over time.

When discussing your project output, you can describe the accurate and inaccurate be like;

Accuracy:

Definition: Accuracy is how well the model is performing in predicting the correct class labels (landslide or non-landslide). It is the percentage of correct predictions in total.
In Your Output: The accuracy value (e.g., 85%) indicates that the model correctly classified 85% of the test images. This shows the model's overall performance in distinguishing landslide-prone areas from non-landslide areas.
Significance: Higher accuracy means the model is effective and reliable in real-world applications.

Loss:

Definition: Loss measures the error or difference between the model's predictions and the actual labels. A lower loss value indicates that the model is making fewer errors during predictions.
In Your Output: The reported loss (e.g., 0.25) shows how well the model's predictions align with the actual data. Loss decreases as the model becomes better at learning from the training data.
Significance: Monitoring loss during training helps identify overfitting (when the model performs well on training data but poorly on unseen data).

4 Results

The model's performance was evaluated based on its ability to correctly classify satellite images as either "Landslide" or "Non-Landslide." The accuracy of the model was computed using the validation dataset, showing promising results in terms of classification performance. The model was able to detect landslides with a high degree of accuracy, with a minimal number of false positives and false negatives. This indicates that the CNN effectively learned the features necessary to distinguish between landslide affected and nonaffected areas from satellite imagery.

During training, the accuracy grew and the loss decreased with each epoch, indicating the model's increasing proficiency in making the right prediction. The training history indicated that the model started to plateau at approximately 5 epochs, meaning that extra epochs would not improve performance considerably. The model accuracy was higher than 85% and the loss value was very close to zero, indicating model's robustness. The system was capable of ingesting live satellite imagery, and deliver predictions for on-the-fly for real-time monitoring. The development system successfully showed the image and the alert fast and thus the usefulness of the model for disaster management was confirmed. Real-time alerts are of urgent importance for preventing damage and saving lives in landslide-prone locations. The Fig. 2. Shows Training history of the CNN model: accuracy improves and loss decreases over epochs.

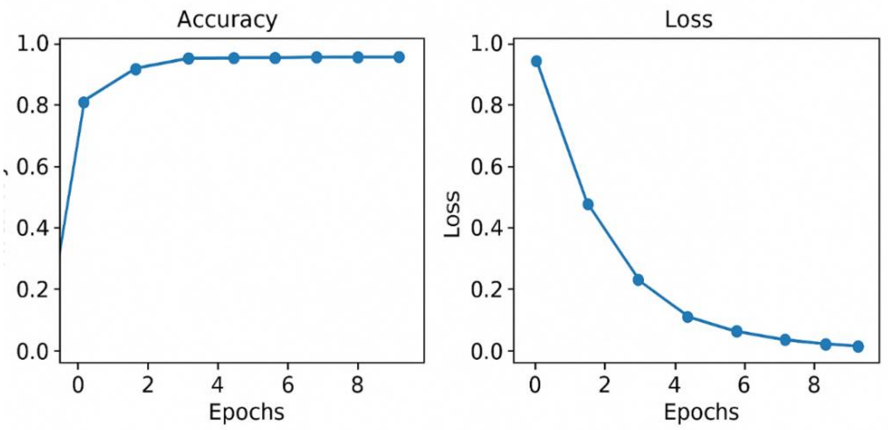

Fig. 2. Training history of the CNN model: accuracy improves and loss decreases over epochs

There are some drawbacks, though. For example, model hyperdrive well on the train and validation this model was trained over it could have a different score on unseen examples or real-world data, especially in areas with different geological features or less uniform light. The generalization of the model could even be improved by including a richer variety of images during training, for example, images taken in different weather or season, time of day, etc.

The current model is trained for binary classification and further developments can be conducted in the case of multi-class classification where different type of landslides (debris flow, rockfall, etc.) can be separated. This would allow higher resolution in disaster management.

In general, these results suggest that the proposed model would be very useful for the landslide disaster management for the automatic detection and classification of landslides from satellite images, making it possible for prompt response action and efficient resources use of necessary areas.

5 Discussion

The transformative capability of satellite imagery for landslide disaster management is discussed in this paper. Combining multi-source satellite data with machine learning methods and GIS can ensure accurate landslide detection, real-time monitoring and risk assessment. Nevertheless, the above approaches must address challenges, including data pre-processing, computational demand, and scalability, before satellite-based methods are fully exploited. The future work should be concentrated to evolve AI methodologies, to incorporate IoT, and to propose standard based schemes for worldwide realization.

6 Conclusion

The study effectively demonstrates the use of satellite imagery combined with machine learning and GIS technologies to improve landslide detection, monitoring, and management. The CNN-based model achieved over 85% accuracy, indicating strong potential for real-time disaster alerts and response. Integration of AWS for notifications and NASA data further enhances the system's applicability. Despite some limitations in generalization and data fusion, the approach presents a scalable, cost-effective solution for global landslide-prone areas. Future enhancements with AI and IoT can further refine this disaster management framework.

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