IJITCE

ISSN 2347- 3657

International Journal of
Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

MACHINE LEARNING ALGORITHMS FOR LANDSLIDE DETECTION AND FORECASTING USING SATELLITE IMAGERY

[1] A Hima Bindu, MCA Student, Department of MCA

[2] Dr.Dhanraj Cheelu, Ph.D, Professor, Department of MCA

[12]Dr KV Subba Reddy Institute of Technology, Dupadu, Kurnool

ABSTRACT

Landslides in steep regions may be caused by man-made elements such unforeseen structures or natural ones like excessive rainfall, earthquakes, and soil moisture. Automatic prediction may help prevent landslides, which can be catastrophic and result in significant property and human loss. Recently, landslides have been automatically identified using machine learning techniques. For the semiautomatic identification and prediction of landslides, a variety of feature extraction and classification-based techniques have been used to satellite pictures. Nevertheless, there hasn't been much study on totally automated detection with respectable accuracy. Finding a suitable training database and producing very accurate test results is the most difficult job in the categorisation and prediction of landslides using satellite photos. Finding the research gap is the main goal of a thorough analysis of the many methods utilised for landslip detection and classification using satellite imagery. Proposing a unique strategy prototype for the same job is the secondary goal. For analysis, fifty publications from reputable journals that use machine learning and deep learning algorithms are taken into consideration. The performance of several categorisation methods from current research is compiled in this article, which then compares and discusses their accuracy. An efficient landslip categorisation technique prototype is suggested based on the gap found. Tested using an expanded Beijing dataset of 770 satellite photos, a slightly altered version of the deep learning network ResNet101 produces an accuracy of 96.88%. Additionally, the study gives the researchers an overview, current state, and future directions of machine and deep learning algorithms for landslip detection. The methods covered will be a useful tool for spotting research gaps, mentoring aspiring scholars, and encouraging creative inquiry in the area of satellite image-based landslip categorisation.

I. INTRODUCTION

OVERVIEW OF INTRODUCTION

The protection of infrastructure and human life against natural catastrophes such as earthquakes and landslides is of paramount significance in the modern day. National efforts to ensure the safety of living things in landslide-prone areas are growing as more mountain regions become inhabited. Both property and human life may be severely damaged by landslides. In a variety of nations, landslides provide serious demographic and economic challenges, highlighting the need of proactive risk management and cross-border cooperation to prevent losses from disasters [1]. With the exception of snow-capped regions, 12.6% of India's covered terrain is vulnerable to landslides. The Himalayan range, which is further divided into the Northeast Himalaya and the North West Himalaya, has an area of around 0.32 million square kilometres. The North East Himalayan states of Darjeeling and Sikkim include an area of 0.18 million square kilometres that is vulnerable to landslides. The 0.14 million square kilometres that make up the North West Himalaya include Uttarakhand, Himachal Pradesh, and Jammu & Kashmir. The overall area susceptible to landslides is made up of 0.09

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

million square kilometres from the Western Ghats, which include Tamil Nadu, Kerala, Karnataka, Goa, and Maharashtra, and 0.01 square kilometres from the Eastern Ghats [2]. The Himalayan range is located in earthquake zones IV and V, which are vulnerable to landslides brought on by seismic activity [3]. In the majority of developing nations, landslides are estimated to cause 1-2 percent of GDP in infrastructure loss [4]. Since over 80% of landslide-related deaths are recorded from developing nations, estimating and reducing the damage caused by landslides is a difficult issue for government authorities and technical teams in these nations [5].

A sharp rise in building is followed by developing counties. Roads, railway lines, bridges, tunnels, and other infrastructure link remote locations. Landslides and other ecological dangers are brought on by construction in the morphological region. Geospatial analysis using thematic weighting is used to assess the risk of landslides along road alignments in the North Sikkim Himalayas. In order to lessen the chance of future tragedies, building design is informed by the findings, which indicate that 65.3% of landslides occur in extremely high-hazard zones [6]. Any natural or man-made calamity that results in fatalities is called a landslip. As a growing nation, it is impossible to halt building and regulate the natural factors that cause landslides. As a result, an early warning system may prevent fatalities from these dangers. Artificial intelligence landslip detection models may be trained using pre-processed satellite image datasets to extract features. In the digital age, artificial intelligence (AI) and machine learning are crucial for leveraging diverse data sources and facilitating geographical information analysis for disaster risk reduction. For instance, recurrent and convolutional neural networks have performed assessments with an accuracy of above 90% [7].

The first step in the three-stage process of classifying landslides is gathering photos or building databases using satellite data. First, a region that is prone to landslides is chosen, and satellite photos of landslides and non-landslides associated with that area are gathered and stored in a database. There aren't many readily usable data sets for algorithm testing and training [8]. Preprocessing the gathered data involves segmenting the region of interest, boosting brightness, and eliminating noise. One crucial stage in picture pre-processing is image segmentation. The quality of the photos determines the segmentation's outcome. Reliable segmentation findings from high-resolution photos and machine learning methods are helpful for choosing items of interest [9].

Landslip prediction and catastrophe risk reduction are greatly aided by satellite remote sensing data. Information gathered by remotely sensed satellites aids in maintaining landslip inventory, particularly during risk assessment and landslip prevention [10]. Additionally, satellite data may be used to monitor current ground conditions and provide a warning during crises [11]. Using satellite imagery, machine learning can make it simple and accurate to classify and forecast landslides. The disaster management team can prevent property damage and save lives by anticipating landslip occurrences in advance. Because of the intricate links between landslides and their causal causes, machine learning methods are widely utilised for mapping landslide risk. With an Area Under the Curve (AUC) value greater than 0.90, several machine learning algorithms provide susceptibility maps with excellent reliability [12].

Geological surveys and satellite imaging analysis have historically been used in tandem to identify landslides.

The following are the main goals of this essay.

ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

1. To evaluate and classify various machine learning and deep learning methods and compare their performance using various datasets and satellite types from which precise data is gathered.
2. To determine the research gap in the recently published literature on the machine learning categorisation of landslides.
3. To see whether artificial intelligence methods can better classify data that includes landslides and data that does not.
4. To provide a working prototype of a novel artificial intelligence-based method for more precise landslip categorisation.

This investigation found a number of important issues with this work, including 1. Choosing current and relevant articles from the literature that is accessible.
2. Determine criteria and areas of agreement for assessing and contrasting the effectiveness of current solutions.
3. When comparing various machine learning methods, employ a standard approach.

50 research articles based on machine learning algorithms for automated and semiautomatic landslip categorisation have been chosen for this article from a variety of sources, including IEEE Explore, Springer, the Remote Sensing Journal, the landslip Journal, IEEE, and Science Direct, among others. Enough effort is made to guarantee that the research papers include a range of datasets from different places throughout the globe that are prone to landslides. In order to create a novel, reliable method for reliably predicting landslides from any dataset, the researcher will be able to comprehend the evolving trends of datasets and methodologies.

In order to identify research gaps and provide guidance to new researchers in the field of landslip classification using satellite images, this article compares and discusses the accuracy of various classification techniques obtained from recent literature. Based on the observed deficiency, the study also makes a contribution by putting out an efficient prototype of the landslip categorisation technique. The main contribution of the proposed study is the slightly adjusted and properly calibrated version of the deep learning model ResNet101, which, when evaluated on an enlarged Beijing dataset of 770 satellite photos, produces an accuracy of 96.88%. This is how the rest of the article is organised. The research work is compiled in Section II and arranged by algorithm type. Section III identifies the key results and research needs. Section IV suggests an artificial intelligence-based categorisation system that is optimised based on the identified research need. The articles are concluded in Section V.

Purpose of the Project

Exploring and assessing artificial intelligence methods—specifically, machine learning and deep learning algorithms—for the categorisation and prediction of landslides using satellite data is the main goal of this study. Serious risks to life and property are posed by landslides in mountainous areas, which are often caused by human activity like haphazard building or natural events like intense rains and earthquakes. These dangers may be reduced with the use of early and precise landslip prediction.

This study focuses on:

- Examining 50 recent research publications in-depth to evaluate current AI methods used for landslip prediction and detection.
- Finding research needs, particularly in the field of highly accurate and entirely automated categorisation systems that use satellite imagery.
- Using a modified ResNet101 architecture, a new and efficient deep learning-based prototype model for landslip detection is proposed.
- Using an expanded Beijing dataset of 770 satellite photos, the suggested

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

model was tested and showed a promising accuracy of 96.88%.

II. LITERATURE SURVEY

A. K. Turner, "Landslides' effects on society and the environment," Solutions, Innovation, and Infrastructure

The "movement of a mass of rock, debris, or earth down a slope" is referred to as a landslip. But landslides are not only seen on "land" or during "sliding." Natural occurrences known as landslides disturb society when people position elements of the constructed environment in their path. In mountain valleys and along transportation corridors, slope instability presents risks and causes significant financial losses. The speed of landslides ranges from very slow (a few mm/year) to very fast (more than 5 m/s) spanning 10 orders of magnitude. Landslides that move more quickly than a person can run are likely to cause a significant number of deaths. Buildings atop "very slow" and "extremely slow" landslides, on the other hand, may survive for hundreds of years with little damage and little upkeep. Individual landslides also vary in volume over many orders of magnitude. The "power" (or energy) of a landslip is roughly equal to the product of its volume and speed. It is a helpful indicator of how devastating landslides may be. Even the biggest and most spectacular landslides go unnoticed and hardly ever lead to a national disaster declaration because they are local occurrences. Both direct and indirect expenses are included in landslip losses. Damages that may be directly linked to the landslip are known as direct costs. Travel diversions, financial constraints, and environmental effects are examples of indirect costs. Direct costs are often equal to or greater than indirect expenses. Mitigation refers to actions that stop or lessen the negative consequences of landslides. In order to safeguard endangered populations, mitigation involves administrative, legal, and political actions in addition to structural and geotechnical ones. It is economically, socially, and environmentally necessary to lessen the worldwide effect of landslides on vulnerable communities and vital infrastructure. Loss statistics indicate that while losses are rising globally, the effects are more severe in underdeveloped nations than in wealthy ones.

"Analysis of landslip reactivation using satellite data: A case study of Kotrupi landslip, Mandi, Himachal Pradesh, India," by N. Singh, S. K. Gupta, and D. P. Shukla Spatial Inf. Sci., Remote Sens., Int. Arch. Photogramm.

A common worldwide natural hazard, landslides are caused by inadequate, weak rocks, undulating geography, steep slopes, and constant rainfall. A huge landslip occurred in Kotrupi, Mandi district, Himachal Pradesh, India, during the evening of August 12, 2017. another 50 persons were killed and another 40 were reported missing after the massive fall undermined a 300-meter section of NH-154. According to locals, this region has historically been unstable and has had minor landslides. Google Earth's historical satellite photos from December 2001 to March 2017 showed the landslip scar. This is where a massive landslip happened on August 13, 1977. Satellite photos from 2001 show that on August 13, 1997, after 20 years, the landslip reactivated and parts of the slope collapsed. On August 13, 2007, the landslip reactivated, although little attention was paid to it since it was a minor occurrence with little impact. Once again, ten years later, this landslip was reactivated on the evening of August 12, 2017. The debris that has already collected on the hill and valley sides, as well as the higher reaches of the crown region of the major slide complex, might cause slope instability to recur. Although the site's stability may be determined via geological, geotechnical, and geophysical studies, information for future

https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

preventative actions is obtained by satellite surveillance.

J. Wartman and W. Pollock, "Human susceptibility to landslides," Geo-Health

Every year, landslides kill thousands of people, posing a terrible hazard to human health. Although human vulnerability is a critical component of landslide risk mitigation, all approaches to evaluating the human effects of landslides to far have relied on expert, subjective judgement. Moreover, these approaches don't investigate the root causes of death or guide plans to lower the likelihood of landslides. Given these concerns, we create a data-driven technique that can be used directly to landslip risk assessment, estimating a person's likelihood of dying depending on landslip severity. We discover that human behaviour is the main cause of death between inundation depths of around 1–6 m. Although there is a substantial correlation between landslip susceptibility and a region's economic growth, landslip losses are not categorised by age or gender like other natural disasters. We find that the probabilities of survival are increased by up to a factor of 12 by seemingly basic activities, including going to a higher level or a planned refuge location. Furthermore, educating citizen first responders and implementing community-scale hazard awareness programs are effective ways to increase landslip survival rates.

D. Petley, "Worldwide trends in landslip fatalities," Geology

The number of people killed by landslides worldwide is not well measured. Impacts and geographical distributions may be properly quantified for the first time thanks to a worldwide data collection of deaths from nonseismically generated landslides that caused death between A.D. 2004 and 2010. Over the course of the seven-year investigation, 2620 deadly landslides were reported globally, resulting in 32,322 documented deaths. Analysis of the data indicates that it may still somewhat underestimate the real human costs, even if the overall number of landslides and casualties is an order of magnitude more than what previous data sets have shown. Asia is where most human casualties have place, particularly in China and along the Himalayan Arc. The yearly landslip cycle, which peaks in the summer months in the Northern Hemisphere, is dominated by this geographic concentration. On a national level, the density of landslides is modestly associated with the population density, and the number of deaths per occurrence has a fat-tailed power law distribution.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

1. Malviya and Gupta [13] classified 24 distinct class satellite photos using learning-based Extended Local Binary Patterns [ELBP] and SVM. This research identified two key problems with satellite image processing: noise is more pronounced in satellite pictures, and each satellite image has distinct characteristics. The noise pattern and local binary pattern utilised for segmentation are estimated using the SVM method.
2. Byun et al. [14] presented a multispectral imaging strategy for landcover categorisation that is based on the Seeded Region Growing (SRG) technique. High-resolution pan-sharpened pictures and effective image segmentation algorithms were used. For homogenous picture areas with precise and near bounds, the modified SRG technique integrates the multispectral and gradient information of images. The multi-valued anisotropic diffusion approach was used to gather edge information for the purpose of obtaining local minima and seed points in the noise reduction process of multispectral pictures. For experimental

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

findings, two datasets—Quick Bird picture and GeoEye-1—were employed.

3. To classify multi-frequency pictures from RADARSAT-2 (RS2), Synthetic Aperture Radar (SAR), and Thaichote (THEOS) MS images, Sukawattanavijit et al. [15] created the GA SVM algorithm. The land cover was classified using the SVM classifier. GA was utilised to get the greatest input feature. The fitness of the function was defined by the number of characteristics in the chosen subset and the accuracy of function classification.
4. A multi-feature model-based SVM that integrates many spatial and spectral properties at the object and pixel levels was suggested by Huang and Zhang [16]. Three features were used: an urban complexity index, a co-occurrence matrix, and different morphological profiles Gray-level.
5. Shukla et al. [17] examined one case study on the Garhwal region in order to review several LSZ map methodologies for creating landslip susceptibility zonation maps using support vector machines. The topographical survey of India was used to produce the datasets.
6. In order to categorise the dataset data mining techniques used, Sabanci et al. [18] examined the performance of the K-Nearest Neighbour Algorithm and multilayer perceptron (MLP) for the categorisation of various forest kinds. Three stages of processing were applied to the gathered ASTER satellite image dataset: classification, regression, and clustering, coupled with the use of association rules.
7. Mianji et al. [19] presented a modified supervised classification approach that combines the probabilistic spare kernel method based on Bayesian learning with the feature reduction strategy. Hyperspectral data was initially moved to a low-dimensionality feature space and processed using a multiclass RVMclassifier in order to enhance the distance between the classes.
8. Li et al. [20] looked into the segmentation of hyperspectral images using an active sampling guided Bayesian technique with active learning. For class posterior probability distribution learning, a multinomial logistic regression model based on logic regression was used. The hyperspectral images were segmented and spatial information was encoded using an unbiased multilevel logistic prior (MLP).

Disadvantages

1. Choosing current and relevant articles from the literature that is accessible.
2. Determine criteria and areas of agreement for assessing and contrasting the effectiveness of current solutions.
3. When comparing various machine learning methods, use a standard approach.

PROPOSED SYSTEM

The initial step in the suggested approach for classifying landslides is gathering pictures or building databases from satellite data. First, a region that is prone to landslides is chosen, and satellite photos of landslides and non-landslides associated with that area are gathered and stored in a database. There aren't many readily usable data sets for algorithm testing and training [8]. Preprocessing the gathered data involves segmenting the region of interest, boosting brightness, and eliminating noise. One crucial stage in picture pre-processing is image segmentation. The quality of the photos determines the segmentation's outcome. Reliable segmentation findings from machine learning methods and high resolution photos are helpful for choosing items of interest [9].

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

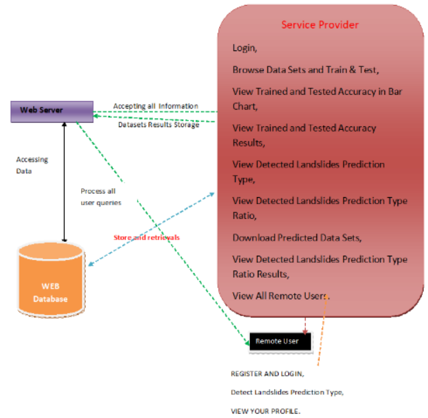
Data from satellite remote sensing is very useful for landslip prediction and catastrophe risk reduction. Information gathered by remotely sensed satellites aids in maintaining landslip inventory, particularly during risk assessment and landslip prevention [10]. Additionally, satellite data may be used to monitor current ground conditions and provide a warning during crises [11]. Using satellite imagery, machine learning can make it simple and accurate to classify and forecast landslides. The disaster management team can prevent property damage and save lives by anticipating landslip occurrences in advance. Because of the intricate links between landslides and their causal causes, machine learning methods are widely utilised for mapping landslide risk. An Area Under the Curve (AUC) value of more than 0.90 indicates that several machine learning algorithms provide susceptibility maps with excellent reliability [12].

Advantages

1. To accurately gather data from a variety of datasets and satellite kinds, classify and analyse various machine and deep learning approaches, and evaluate their performance.
2. To determine the research gap in the recently published literature on the machine learning categorisation of landslides.
3. To see whether artificial intelligence methods can better classify data that includes landslides and data that does not.
4. To provide a novel artificial intelligence-based method prototype for more accurate landslip categorisation.

SYSTEM ARCITECTURE

Architecture Diagram



IV. IMPLEMENTATION

MODULES DESCRIPTION

Service Provider

The Service Provider must use a working user name and password to log in to this module. Following a successful login, he may do several tasks including browsing data sets and training and testing. The following features are available: Downloaded Predicted Data Sets; Viewed Detected Landslides Prediction Type Ratio; Viewed Trained and Tested Accuracy in Bar Chart; Viewed and Tested Accuracy Results; and Viewed All Remote Users.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

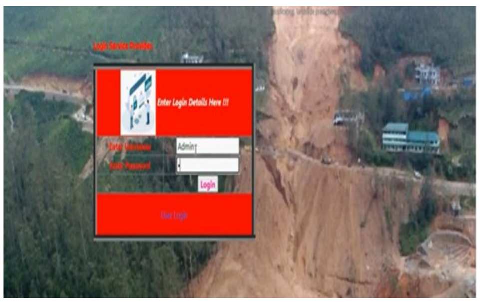
Remote User

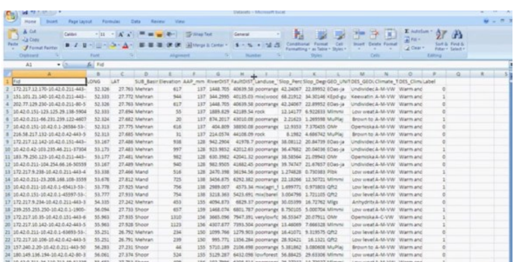
A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. The user will do many tasks after successfully logging in, including registering and logging in,

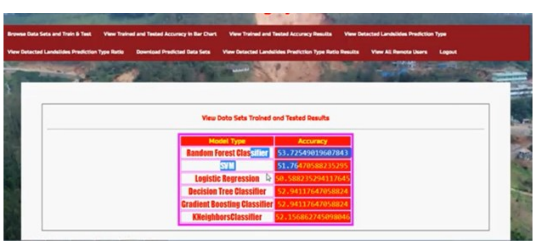
International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

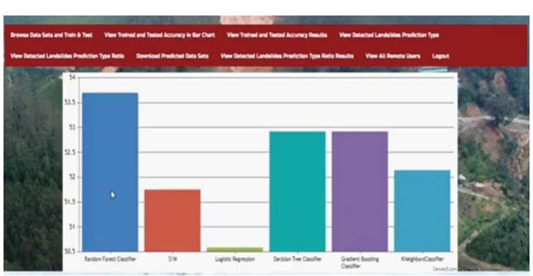
detecting the kind of landslip prediction, and seeing their profile.

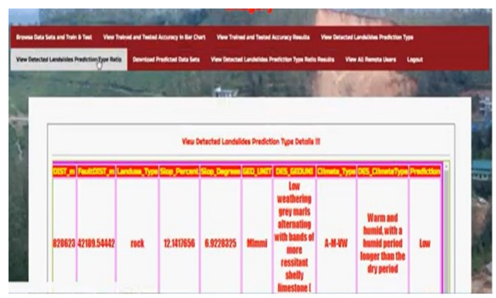
V. SCREEN SHOTS

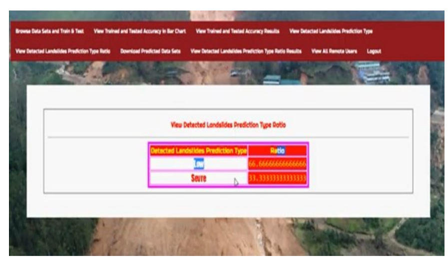


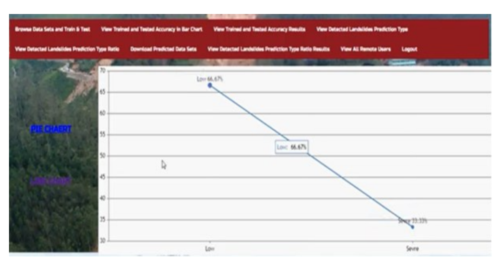










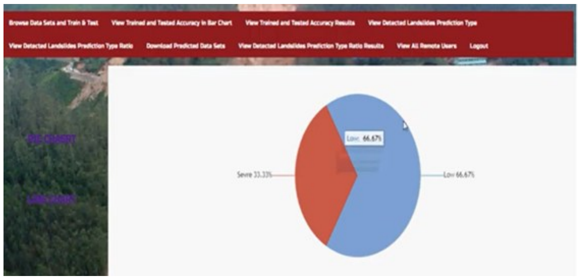


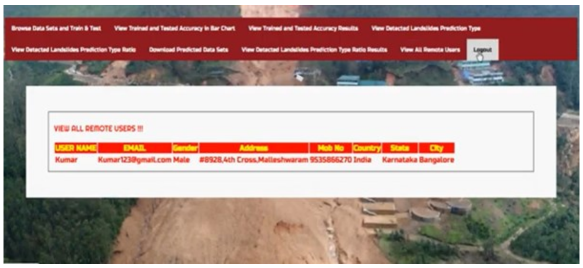
International Journal of Information Technology & Computer Engineering

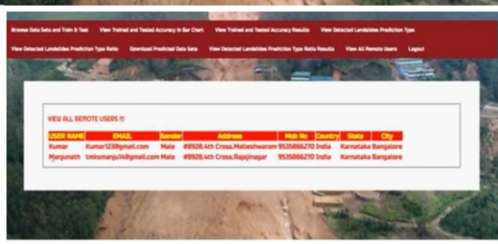
ISSN 2347–3657

Volume 13, Issue 2, 2025

https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369







VI. CONCLUSION

This article uses a variety of satellite image datasets to examine and compare several machine and deep learning methods for landslip identification. Seventy percent of the chosen publications employed passive sensor-based satellite databases, whereas twenty-two percent used active sensor-based databases. In a few chosen articles, the accuracy ranged from 90% to 95%. According to this research, a hybrid mixture of many algorithms produces superior classification results than a single method. A prototype model is suggested along with the identification of the research gap. With carefully calibrated hyperparameters, the suggested model achieves the maximum precision index of 96.4% and the best landslide identification effect with an accuracy value of 96.88% using the deep learning CNN network ResNet101 as the backbone. The findings therefore show that the suggested method may give more accurate landslip data categorisation.

Naturally, this work has certain limits. Future studies might integrate satellite image processing with meteorological data to reduce the limitations and provide a more precise knowledge of landslip prediction and detection. For improved forecast accuracy, environmental factors including soil moisture, precipitation, and seismic activity may also be included in the feature vector. You may utilise the Attention module to further improve the models' performance. The attention process aids in concentrating on environmental elements and key features of satellite images. This might increase the model's resilience and adaptability by enhancing its ability to generalise across various contexts and environments.

REFERENCES

[1] A. K. Turner, ‘‘Social and environmental impacts of landslides,’’ Innov. Infrastruct. Solutions, vol. 3, no. 1, Dec. 2018, Art. no. 70, doi: 10.1007/s41062-018-0175-y.

[2] Landslide Atlas. emphGeological Survey of India. Accessed: Dec. 12, 2023. [Online]. Available: https://www.gsi.gov.in

[3] N. Singh, S. K. Gupta, and D. P. Shukla, ‘‘Analysis of landslide reactivation using satellite data: A case study of Kotrupi landslide, Mandi, Himachal Pradesh, India,’’ Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci., vol. XLII-3, pp. 137–142, Feb. 2020, doi: 10.5194/isprs-archives-xlii-3- w11-137-2020.

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025
https://doi.org/10.62647/ijitce.2025.v13.i2.pp360-369

[4] W. Pollock and J. Wartman, ''Human vulnerability to landslides,'' Geo-Health, vol. 4, no. 10, Oct. 2020, Art. no. e2020GH000287, doi: 10.1029/2020gh000287.

[5] D. Petley, ''Global patterns of loss of life from landslides,'' Geology, vol. 40, no. 10, pp. 927–930, Oct. 2012, doi: 10.1130/g33217.1.

[6] B. Koley, A. Nath, S. Saraswati, S. Bhattacharya, B. C. Ray, T. Choudhury, and J.-S. Um, ''Landslide hazard zones differentiated according to thematic weighting: Road alignment in North Sikkim Himalayas, India,'' Spatial Inf. Res., vol. 32, no. 1, pp. 29–46, Feb. 2024, doi: 10.1007/s41324-023-00533-1.

[7] A. Goel, A. K. Goel, and A. Kumar, ''The role of artificial neural network and machine learning in utilizing spatial information,'' Spatial Inf. Res., vol. 31, no. 3, pp. 275–285, Jun. 2023, doi: 10.1007/s41324-022-00494-x.

[8] A. Sharma, K. K. Sharma, and S. G. Sapate, ''A prototype model for detection and classification of landslides using satellite data,'' J. Phys., Conf. Ser., vol. 2327, no. 1, 2022, Art. no. 012029, doi: 10.1088/1742-6596/2327/1/012029.

[9] S. Dridi, ''Unsupervised learning—A systematic literature review,'' Tech. Rep., 2021, doi: 10.13140/RG.2.2.16963.12323.

[10] N. Casagli, F. Cigna, S. Bianchini, D. Hölbling, P. Füreder, G. Righini, S. D. Conte, B. Friedl, S. Schneiderbauer, C. Iasio, J. Vlcko, V. Greif, H. Proske, K. Granica, S. Falco, S. Lozzi, O. Mora, A. Arnaud, F. Novali, and M. Bianchi, ''Landslide mapping and monitoring by using radar and
optical remote sensing: Examples from the EC-FP7 project SAFER,''Remote Sens. Appl., Soc. Environ., vol. 4, pp. 92–108, Oct. 2016, doi:10.1016/j.rsase.2016.07.001.

[11] M. M. Jaber, M. H. Ali, S. K. Abd, M. M. Jassim, A. Alkhayyat, B. A. Alreda, A. R. Alkhuwaylidee, and S. Alyousif, ''A machine learning-based semantic pattern matching model for remote sensing data registration,'' J. Indian Soc. Remote Sens., vol. 50, no. 12, pp. 2303–2316,
Dec. 2022, doi: 10.1007/s12524-022-01604-w.

[12] M. Ado, K. Amitab, A. K. Maji, E. Jasińska, R. Gono, Z. Leonowicz, and M. Jasiński, ''Landslide susceptibility mapping using machine learning: A literature survey,'' Remote Sens., vol. 14, no. 13, p. 3029, Jun. 2022, doi: 10.3390/rs14133029.

[13] U. K. Malviya and R. Gupta, ''Satellite image classification method using ELBP and SVM classifier,'' in Proc. Int. Conf. Adv. Electr., Comput., Commun. Sustain. Technol. (ICAECT). Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Feb. 2021, pp. 1–6, doi:
10.1109/ICAECT49130.2021.9392509.

[14] Y. G. Byun, Y. K. Han, and T. B. Chae, ''A multispectral image segmentation approach for object-based image classification of high resolution satellite imagery,'' KSCE J. Civil Eng., vol. 17, no. 2, pp. 486–497, Mar. 2013, doi: 10.1007/s12205-013-1800-0.

[15] C. Sukawattanavijit, J. Chen, and H. Zhang, ''GA-SVM algorithm for improving land-cover classification using SAR and optical remote sensing data,'' IEEE Geosci. Remote Sens. Lett., vol. 14, no. 3, pp. 284–288, Mar. 2017, doi: 10.1109/LGRS.2016.2628406.