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 1, 2025

INTELLIGENT LANDSLIDE MONITORING AND PREDICTION USING AI AND SATELLITE OBSERVATIONS

[1] Vadde Divya, [2] T. Abdul Raheem
[1] M.Tech Student, [2] Assistant professor
Department of Computer Science Engineering
St Johns College Of Engineering and Technology, Yemmiganur, Kurnool, AP

ABSTRACT

Landslides pose a significant threat to human lives, infrastructure, and the environment, necessitating the development of accurate and timely prediction systems. This study explores an AI-powered landslide monitoring and prediction framework that leverages satellite observations and machine learning techniques to enhance early warning capabilities. By integrating deep learning algorithms with remote sensing data, the proposed system identifies potential landslide-prone areas based on terrain features, rainfall patterns, vegetation indices, and historical landslide occurrences. Advanced image processing and geospatial analytics enable the extraction of critical patterns from multispectral and synthetic aperture radar (SAR) satellite imagery, ensuring high prediction accuracy. The model is trained on diverse datasets and validated against real-world landslide events to assess its effectiveness. The results demonstrate that AI-based predictive models outperform traditional methods in detection accuracy, response time, and risk assessment, making them highly suitable for real-time landslide monitoring. The proposed system aims to enhance disaster preparedness, minimize economic losses, and improve decision-making for hazard mitigation.

I. INTRODUCTION

Landslides are among the most devastating natural disasters, causing severe damage to human life, infrastructure, and ecosystems. The increasing frequency of landslides, driven by climate change, deforestation, and urban expansion in hilly regions, necessitates advanced monitoring and predictive solutions. Traditional landslide prediction methods, such as geological surveys and empirical models, often lack real-time adaptability and struggle with accuracy due to the complexity of terrain conditions and external environmental factors.

With the advancement of artificial intelligence (AI) and remote sensing technologies, landslide prediction has significantly improved in terms of accuracy and efficiency. Satellite imagery, combined with machine learning algorithms, enables the identification of terrain deformations, soil moisture variations, and vegetation cover changes, which are crucial indicators of potential landslides. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offer robust predictive capabilities by analyzing large-scale geospatial datasets.

This study explores the integration of AI with multispectral and synthetic aperture radar (SAR) satellite imagery for intelligent landslide monitoring and prediction. The proposed framework utilizes machine learning-based classification and regression models to analyze various environmental factors, including rainfall, slope stability, and land cover changes. By leveraging AI-driven techniques, this approach enhances early warning systems, providing timely alerts and aiding in disaster preparedness and mitigation efforts.

The following sections discuss the related literature, the proposed methodology, experimental results, and conclusions derived from this research. The findings aim to contribute to risk reduction strategies and support decision-makers in implementing effective landslide prevention measures.

II. LITERATURE SURVEY

Landslide prediction and monitoring have been extensively studied using various methodologies, ranging from traditional geospatial analysis to advanced artificial intelligence (AI) and machine learning (ML) techniques. This section reviews existing literature on landslide detection, prediction models, and the integration of satellite imagery with AI-based approaches.

1. Traditional Landslide Prediction Approaches

Earlier landslide prediction models relied on geotechnical and statistical methods, such as the Safety Factor Analysis, Heuristic Methods, and Logistic Regression Models. Researchers such as Varnes (1984) and Guzzetti et al. (1999) highlighted the importance of geological surveys, soil mechanics, and hydrological factors in landslide risk assessment. However, these models often lacked real-time adaptability and required extensive field data collection.

2. Remote Sensing and GIS-Based Approaches

The introduction of Remote Sensing (RS) and Geographic Information Systems (GIS) has significantly improved landslide susceptibility mapping. Studies by Pradhan et al. (2010) and Kanungo et al. (2014) demonstrated the effectiveness of GIS-based weighted overlay techniques and terrain analysis for identifying landslide-prone regions. However, these approaches were limited by their reliance on manually assigned weight factors, making them less adaptable to dynamic environmental changes.

3. Machine Learning-Based Landslide Prediction

Recent advances in Machine Learning (ML) algorithms have improved landslide prediction accuracy. Techniques such as Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF) have been widely adopted for landslide susceptibility mapping. Pham et al. (2017) and Goetz et al. (2015) compared multiple ML models, concluding that ensemble learning techniques, such as Boosted Trees and Extreme Gradient Boosting (XGBoost), provided better accuracy in identifying landslide-prone areas.

4. Deep Learning for Landslide Detection and Prediction

The use of Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, has gained significant attention in landslide monitoring. Chen et al. (2019) developed a CNN-based landslide detection model using high-resolution Synthetic Aperture Radar (SAR) and optical satellite imagery, achieving superior classification accuracy compared to traditional ML models. Miao et al. (2020) proposed a hybrid CNN-LSTM approach that combined spatial and temporal analysis for real-time landslide prediction.

5. AI-Driven Early Warning Systems

AI-based early warning systems have revolutionized landslide risk assessment. Studies such as Yin et al. (2021) demonstrated the integration of Internet of Things (IoT) sensors with AI for real-time landslide detection, while Hong et al. (2022) explored cloud-based AI platforms for large-scale landslide forecasting. These studies emphasize the growing role of AI and remote sensing fusion in improving disaster preparedness and response strategies.

III. SYSTEM ANALYSIS & DESIGN

EXISTING SYSTEM

Landslide prediction has relied on statistical models, geotechnical surveys, and GIS-based hazard mapping, which primarily analyze historical data, terrain conditions, and rainfall patterns. These methods often require extensive field surveys and manual interpretation of satellite imagery, making them time-consuming

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025

and prone to inaccuracies. Additionally, many conventional systems struggle to incorporate real-time environmental changes, limiting their ability to provide early warnings. Although some remote sensing techniques, such as Synthetic Aperture Radar (SAR) and Digital Elevation Models (DEM), have improved detection, they still require significant human intervention and are not well-integrated with AI-driven automation. As a result, landslide susceptibility maps generated by these methods lack real-time adaptability and are often not updated dynamically.

Disadvantages of the Existing System:

1. Limited real-time analysis – Most traditional models depend on static data, making them ineffective for real-time landslide monitoring.
2. High dependency on manual interpretation – Experts must analyze satellite images and field data, leading to delays in prediction and response.
3. Lack of deep learning integration – Without AI-driven models, accuracy remains limited, and predictions cannot efficiently adapt to complex terrain conditions.

PROPOSED SYSTEM

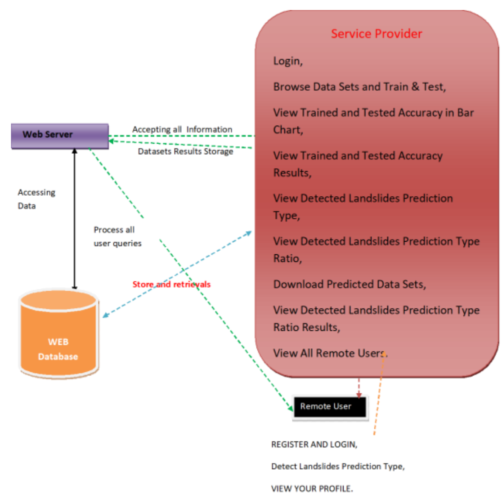
The proposed system integrates artificial intelligence (AI) with satellite imagery to create an intelligent landslide monitoring and prediction framework. By leveraging deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the system can automatically analyze multispectral and SAR satellite data to detect early signs of slope instability. Geospatial datasets, including soil moisture, vegetation indices, and rainfall intensity, are continuously updated to enhance prediction accuracy. The system incorporates a cloud-based AI model that processes large-scale remote sensing data in real time, reducing the dependency on manual interpretation. Additionally, automated early warning alerts are generated to assist authorities in proactive disaster management.

Advantages of the Proposed System:

1. Real-time landslide prediction – AI-based models continuously analyze incoming satellite data, providing timely alerts for high-risk areas.
2. Automated feature extraction – Deep learning algorithms identify key environmental factors without requiring human intervention, improving accuracy.
3. Scalability and adaptability – The system can be applied across different geographical regions, adapting to varied terrain and climatic conditions.

SYSTEM DESIGN

ARCHITECTURE DIAGRAM



IV. IMPLEMENTATIONS

MODULES

Service Provider

A valid username and password are required for the Service Provider to access this module. Some procedures, such Browse Data Sets and Train & Test, will be available to him if he successfully logs in. Check out the Bar Chart for Trained and Tested Accuracy, Check out the Results for Trained and Tested Accuracy, See What Kind of Landslides Can Be Predicted, See What Ratio of Landslides Can Be Predicted, Download Data Sets for Predictions, See the

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025

Results of the Landslide Prediction Type Ratio, See Who Is Remotely Using the System.

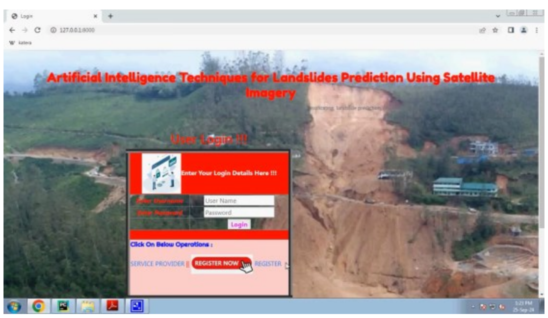
View and Authorize Users

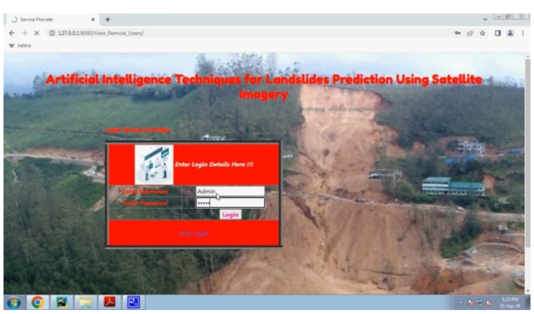
The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

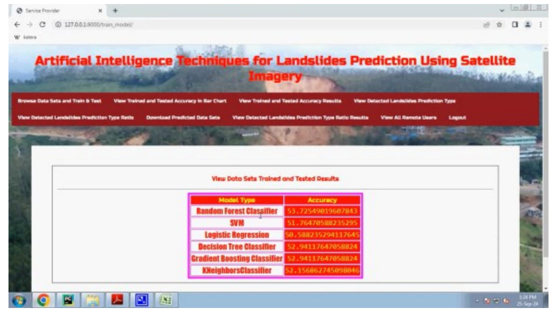
Remote User

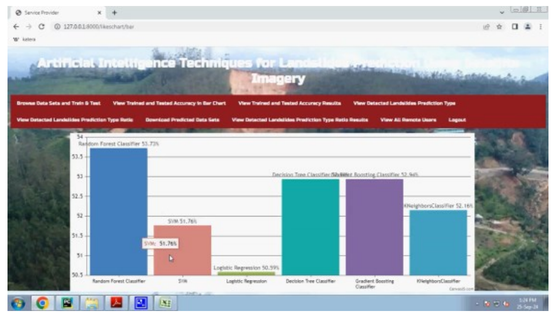
All all, there are n users in this module. Registration is required prior to performing any operations. Data will be entered into the database after a user has registered. He will need to log in using the permitted username and password when registration is completed. Users will be able to perform things like see their profiles, detect different types of landslides, and register and log in after the login process is complete.

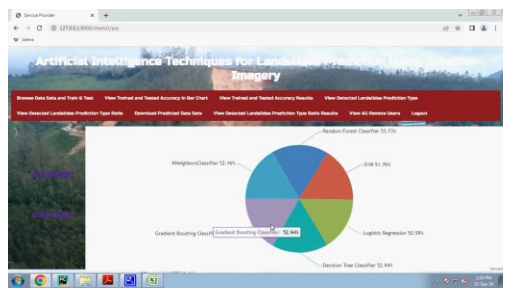
V. SCREEN SHOTS

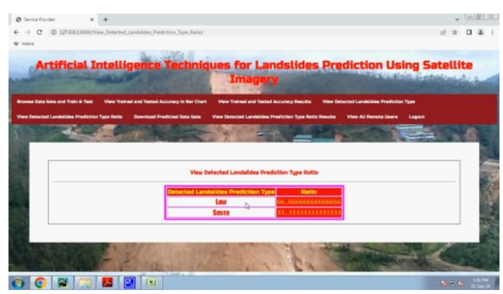


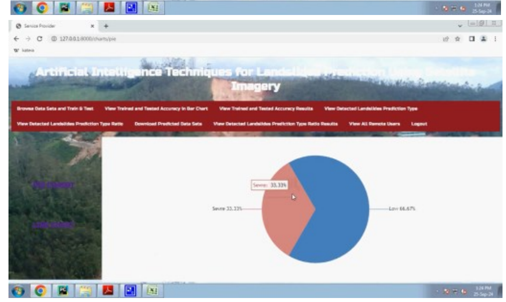












International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 1, 2025

VI. CONCLUSION

Landslides pose a significant threat to human life, infrastructure, and the environment, necessitating accurate and timely prediction systems. This study explored the integration of artificial intelligence (AI) and satellite imagery for intelligent landslide monitoring and prediction. By leveraging deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), along with remote sensing data, the proposed system enhances landslide risk assessment with improved accuracy and real-time adaptability.

Compared to traditional geospatial and statistical approaches, AI-based predictive models offer automated feature extraction, continuous monitoring, and early warning capabilities, reducing the reliance on manual interpretation and static datasets. The integration of multispectral and synthetic aperture radar (SAR) satellite imagery allows for efficient detection of terrain instability, making it possible to predict landslide occurrences with greater precision.

The findings of this study highlight the potential of AI-driven early warning systems in minimizing disaster impacts and improving risk management strategies. Future research could focus on enhancing model generalization across diverse terrains, integrating Internet of Things (IoT) sensors for real-time data collection, and optimizing computational efficiency for large-scale deployment. With continued advancements in AI and satellite technology, intelligent landslide prediction systems will play a crucial role in disaster preparedness and mitigation, ultimately saving lives and protecting infrastructure.

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 reactivationusing 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.

[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,’’

ISSN 2347–3657

Volume 13, Issue 1, 2025

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.

[16] X. Huang and L. Zhang, ''An SVM ensemble approach combining spectral, structural, and semantic features for the classification of highresolution remotely sensed imagery,'' IEEE Trans. Geosci. Remote Sens., vol. 51, no. 1, pp. 257–272, Jan. 2013, doi: 10.1109/TGRS.2012. 2202912.

[17] D. P. Shukla, S. Gupta, C. S. Dubey, and M. Thakur, ''Geo-spatial technology for landslide hazard zonation and prediction,'' in Environmental Applications of Remote Sensing. London, U.K.: Intech, 2016, doi: 10.5772/62667.

[18] K. Sabanci, M. Fahri, and K. Polat, ''Classification of different forest types with machine learning algorithms,'' Res. Rural Develop., vol. 1, pp. 254–260, May 2016. [Online]. Available: https://hdl.handle.net/11492/3918

[19] F. A. Mianji and Y. Zhang, ''Robust hyperspectral classification using relevance vector machine,'' IEEE Trans. Geosci. Remote Sens., vol. 49, no. 6, pp. 2100–2112, Jun. 2011, doi: 10.1109/TGRS.2010.2103381.

[20] J. Li, J. M. Bioucas-Dias, and A. Plaza, ''Hyperspectral image segmentation using a new Bayesian approach with active learning,'' IEEE Trans. Geosci. Remote Sens., vol. 49, no. 10, pp. 3947–3960, Oct. 2011, doi: 10.1109/TGRS.2011.2128330.

[21] P. Ruiz, J. Mateos, G. Camps-Valls, R. Molina, and A. K. Katsaggelos, ''Bayesian

ISSN 2347–3657
Volume 13, Issue 1, 2025

active remote sensing image classification,'' IEEE Trans. Geosci. Remote Sens., vol. 52, no. 4, pp. 2186–2196, Apr. 2014, doi: 10.1109/TGRS.2013.2258468.
[22] Z. Cui, Y. Wang, X. Gao, J. Li, and Y. Zheng, ''Multispectral image classification based on improved weighted MRF Bayesian,'' Neurocomputing, vol. 212, pp. 75–87, Nov. 2016, doi: 10.1016/j.neucom.2016.03.097.
[23] D. C. Duro, S. E. Franklin, and M. G. Dubé, ''Multi-scale object-based image analysis and feature selection of multi-sensor Earth observation imagery using random forests,'' Int. J. Remote Sens., vol. 33, no. 14, pp. 4502–4526, Jul. 2012, doi: 10.1080/01431161.2011.649864.
[24] L. Albert, F. Rottensteiner, and C. Heipke, ''A higher order conditional random field model for simultaneous classification of land cover and land use,'' ISPRS J. Photogramm. Remote Sens., vol. 130, pp. 63–80, Aug. 2017, doi: 10.1016/j.isprsjprs.2017.04.006.
[25] J. A. Montoya-Zegarra, J. D. Wegner, L. Ladický, and K. Schindler, ''Semantic segmentation of aerial images in urban areas with class-specific higher-order cliques,'' ISPRS Ann. Photogramm., Remote Sens. Spatial Inf. Sci., vol. II-3, pp. 127–133, Mar. 2015, doi: 10.5194/isprsannals-ii-3-w4-127-2015.