International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

A Cloud-Based Hybrid CNN-LSTM System for Real-Time Landslide Prediction Using Geospatial Intelligence

Mrs. Swati Chilpunkar[1], Mrs. Monisha Linkesh[2], Dr. Namdeo Badhe[3], Dr. Anil Vasoya[4]

[1,2]Assistant Professor, Department of IT, Thakur College of Engineering & Technology, Mumbai.
[3,4]Associate Professor, Department of IT, Thakur College of Engineering & Technology, Mumbai.

Abstract

Landslides pose a significant threat to life, infrastructure, and economic stability, especially in rainfall-prone and geologically sensitive regions. In this study, we propose a cloud-based landslide prediction system that integrates geospatial data processing with a hybrid deep learning approach. The system begins with the creation of a landslide susceptibility dataset using Quantum GIS (QGIS), incorporating both static (e.g., slope, elevation, land use) and dynamic (e.g., rainfall) environmental features. A hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model is developed to capture spatial patterns and temporal dependencies, offering improved prediction accuracy over conventional models. The system is deployed as a web-based application using HTML, JavaScript, and MySQL, with the backend hosted on Google Cloud Platform (GCP) for scalability and real-time performance. Testing with hybrid pretrained models further enhances prediction reliability. This research demonstrates the effectiveness of combining geospatial tools and deep learning for early warning and disaster mitigation in landslide-prone areas. The proposed system has strong potential for integration into national disaster management frameworks to support timely and data-driven decision-making.

Keywords: Landslide Prediction, Hybrid CNN-LSTM Model,Geospatial Data Analysis,real-Time Early Warning System,Cloud Computing (Google Cloud Platform)

Introduction:

Landslides in the Konkan region of Maharashtra have become a major concern, causing extensive damage to roads, buildings, and critical infrastructure. The situation has worsened in recent years due to rapid urbanization and large-scale land clearing, which have destabilized the terrain and increased the frequency and intensity of landslides. In July 2021 alone, more than 10,000 landslides were reported across the state, reflecting the severity of the crisis. The Ratnagiri district, particularly the talukas of Mahad, Chiplun, Khed, and Poladpur, was among the worst affected, experiencing torrential monsoon rains that triggered numerous slope failures. The Geological Survey of India (GSI) has identified 225 villages in the state as vulnerable to landslides, and it estimates that nearly 30% of Maharashtra is prone to such disasters. Given this alarming scenario, the implementation of early warning systems is crucial. These systems can play a vital role in protecting both human lives and infrastructure by providing timely alerts, enabling authorities

and communities to take preventive measures and evacuate high-risk areas when necessary.
To effectively reduce the impact of landslides in the Konkan region, a comprehensive approach must be adopted that targets both prevention and preparedness. One of the primary concerns is the extensive damage to roads, buildings, and essential infrastructure caused by frequent landslides, especially in areas undergoing rapid urbanization and widespread land clearing. These human activities destabilize natural slopes, making them more susceptible to failure during heavy rainfall. Therefore, strict land-use regulations, reforestation, and environmentally conscious development practices are essential to mitigate such risks.
A focused strategy should be implemented in the most vulnerable areas, particularly in the Ratnagiri district, where talukas like Mahad, Chiplun, Khed, and Poladpur were among the worst affected during the monsoon of 2021. These regions experience intense rainfall, which significantly increases the risk of landslides. Moreover, the Geological Survey of India (GSI) has identified 225 villages across Maharashtra as highly susceptible to landslides. These communities must be prioritized for risk reduction efforts, such as slope stabilization, drainage improvements, and community awareness programs.
In addition to structural and policy-based interventions, the implementation of early warning systems plays a critical role in minimizing the loss of life and property. By monitoring rainfall patterns, soil moisture levels, and ground movements, these systems can provide timely alerts to residents and local authorities. This allows for preemptive evacuation and other safety measures before a disaster occurs. Investing in such technology, along with educating communities about response protocols, will greatly enhance disaster preparedness and resilience in landslide-prone regions.
Literature Survey : Praveen Kumar Rai et al [1] examines the use of remote sensing and GIS for landslide hazard analysis. Using satellite imageries and topographical sheets, the study analyzes parameters like slope, drainage density, and land use. The methodology involves creating Landslide Susceptibility Zonation (LSZ) maps with tools like Digital Elevation Models (DEM). Case studies in Garhwal Himalaya and Southern Mizoram are presented. Challenges include data quality, methodological consensus, and the complexity of modeling landslides. The study also notes the impact of deforestation and construction on landslide incidence.
The paper [2] proposes an automatic disaster detection system using convolutional neural networks (CNN) to analyze satellite images, focusing on landslides and floods in Japan and Thailand. The methodology involves creating training patches from pre-disaster and post-disaster images, labeling them based on changes, and training a CNN to detect disaster regions. The study identifies gaps in previous methods, such as limited sensor ranges and the challenge of processing massive amounts of satellite images. Challenges include ensuring image alignment and handling color variations due to different weather conditions. The results show an accuracy of 80%-90%, highlighting the system's potential for efficient disaster detection.
The study by Naruephorn Tengtrairat et al [3] introduced a novel geographic information web (GIW) application using a bidirectional long short-term memory (Bi-LSTM) algorithm for landslide-risk prediction in Chiang Rai, Thailand. The dataset included static factors like land cover, soil properties, elevation, and slope, along with a dynamic factor, precipitation. The Bi-LSTM model, combined with Random Forest (Bi-LSTM-RF), showed superior performance, improving prediction accuracy over traditional models. Despite these advancements, challenges remain, such as the need for large and diverse datasets, handling imbalanced data, and the complexity of integrating various data sources. Future research should focus on enhancing model robustness, exploring new data sources, and developing more

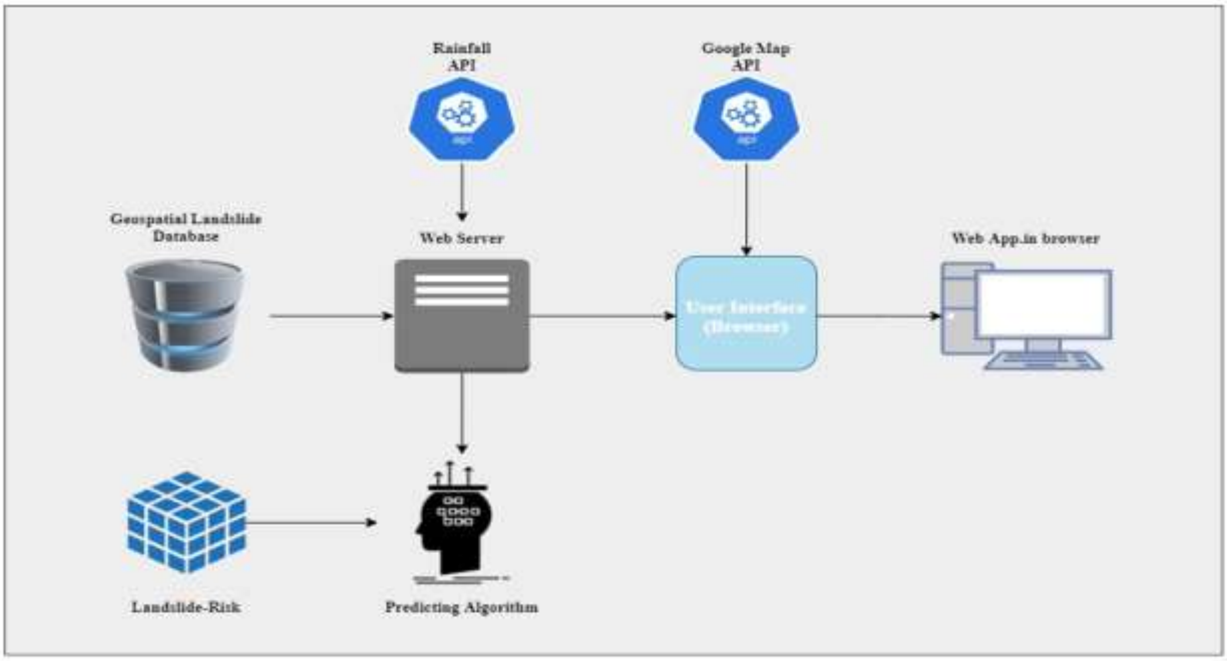
efficient algorithms to address these gaps.
The study "Landslide Identification Using Machine Learning" by Haojie Wang et al [4], explores the integration of machine learning (ML) and deep learning (DL) for identifying landslides using geospatial data. The authors demonstrate that a convolutional neural network (CNN) with 11 layers achieves a remarkable 92.5% accuracy, outperforming other algorithms. Key predictors identified include slope gradient, curvature, and aspect. However, the study is limited by the scope of data, as digital terrain models (DTM) and optical remote sensing may overlook landslide variability. Additionally, the accuracy for relict landslides is constrained by historical data quality. Challenges include the computational complexity of deeper CNN models, data availability for relict landslides, and generalizability to other regions.
The article "Deep Neural Network Utilizing Remote Sensing Datasets for Flood Hazard Susceptibility Mapping in Brisbane, Australia " by Bahareh Kalantar et al [5], presents a PSO-DLNN model achieving a high performance with an AUC of 0.99. Significant predictors are identified as altitude, slope, curvature, distance from rivers, and rainfall, with validation conducted in the Brisbane River catchment area. The study highlights gaps such as limited validation across diverse conditions, the impact of climate change and urbanization, and the computational complexity of real-time applications. Challenges include data quality and availability of high-resolution remote sensing, generalizing the model to other areas, and the need for real-time flood prediction.
In "Landslide Susceptibility Mapping Using Ant Colony Optimization Strategy and Deep Belief Network in Jiuzhaigou Region," Yibing Xiong et al [6], propose an ensemble model combining ant colony optimization (ACO) and deep belief networks (DBN) that achieves 93.11% accuracy in the Jiuzhaigou region. The model optimizes 16 causative factors but faces limitations such as dependency on manual parameter adjustments, limited validation across other regions, and insufficient data on dynamic environmental factors. Key challenges include the computational complexity of combining ACO and DBN, data quality for training, and generalization to regions with varying geological conditions.
Viet-Ha Nhu, Ayub Mohammadi, and Himan Shahabi’s study "Landslide Susceptibility Mapping Using Machine Learning Algorithms and Remote Sensing Data in a Tropical Environment," [7], reveals that the Random Forest algorithm outperforms others. Integrating remote sensing data significantly enhances model accuracy, with slope, land cover, and rainfall identified as key predictors. However, limitations include geospatial data constraints in dense vegetation, temporal inconsistencies in rainfall data, and the model’s transferability to other regions. Challenges focus on the availability and quality of remote sensing data, model scalability, and integration of diverse datasets.
"Machine Learning-Based Landslide Prediction System for Hilly Areas," authored by R. Archana Reddy et al [8], achieves a 94.6% accuracy in landslide prediction using logistic regression (LR). Machine learning methods are shown to outperform conventional rainfall threshold techniques, utilizing data from 2009–2019. The study’s scope is limited by its geographical specificity and transferability to other terrains or climates, alongside inconsistencies in data quality. Computational demands of training ML models, real-time application for early warning, and model interpretability are identified as primary challenges.
The paper "Automated Landslide-Risk Prediction Using Web GIS and Machine Learning Models" by Naruephorn Tengtrairat et al., published in Sensors in 2021, presents an automated prediction model using a Bi-LSTM-RF framework. This model integrates rainfall, topography, land cover, and soil data for risk prediction while providing real-time visualization through Web GIS. The study is limited by a small dataset of three historical cases, lack of dynamic factors like human activities, and challenges in

generalizing the model to other regions. Issues include data integration, computational complexity for real-time predictions, and scalability to larger datasets.
Kounghoon Nam and Fawu Wang's study, "An extreme rainfall-induced landslide susceptibility assessment using autoencoder combined with random forest in Shimane Prefecture, Japan," [10], combines stacked and sparse autoencoders with random forest (RF) to achieve high prediction accuracy of 93.2% and 92.5%. Key predictors include NDVI, altitude, and proximity to roads, with autoencoders enhancing feature extraction and dimensionality reduction. The study's limitations include reliance on a dataset of 90 landslides, spatial bias near roads, and lack of advanced imagery data integration. Challenges involve high computational demand, dependence on quality input data, and limited scalability across diverse terrains.
In "Evaluation of Different ML Models and a Novel Deep Learning Algorithm for Landslide Susceptibility Mapping," Tingyu Zhang et al [11], introduce LSNet, a novel multi-channel CNN model that achieves 95% accuracy, surpassing SVM and KLR models. Key predictors include elevation, slope, and NDVI. The model's multi-channel layers enhance spatial feature integration, validated in Hanyin County, China. Limitations involve reliance on data quality, high computational requirements, and regional biases. Challenges include scalability, external validation, and low interpretability of CNN models.
The research gaps identified across the reviewed studies on landslide and flood hazard prediction highlight several common and critical challenges. A prominent issue is data quality and availability, particularly in remote sensing and geospatial datasets. Many studies face limitations due to low-resolution imagery, inconsistent rainfall data, and inadequate historical records, especially for relict or less visible landslides. Another significant gap is the lack of generalizability and transferability of models across different geographic regions and terrains. Models trained in specific locations often perform poorly when applied elsewhere due to variations in environmental and geological conditions.
Model scalability and computational complexity also emerge as key concerns. Advanced models, such as deep neural networks (DNNs), convolutional neural networks (CNNs), and ensemble approaches, although highly accurate, demand substantial computational resources, making real-time implementation and large-scale deployment difficult. Furthermore, interpretability of deep learning models remains limited, reducing their usability in practical disaster management scenarios where transparent decision-making is essential.
Several studies also suffer from limited validation datasets and narrow case studies, which restrict the robustness and reliability of their predictions. The integration of dynamic factors, such as human activities, deforestation, urbanization, and the effects of climate change, is either missing or inadequately addressed in most models. Lastly, manual parameter tuning, imbalanced datasets, and challenges in data integration from diverse sources further hinder the development of universally applicable and automated prediction systems. Addressing these gaps requires improved data collection strategies, development of more efficient and interpretable algorithms, and validation of models across wider spatial and temporal scales.
The Ratnagiri district has adopted a Real-Time Data Acquisition (RTDA) System as an essential component of its flood and landslide risk management strategy. Installed in rainfall-prone villages and towns, the RTDA system continuously monitors and collects real-time data on key environmental parameters such as rainfall intensity and water levels. This system acts as an early warning mechanism, issuing timely alerts to residents when thresholds indicating potential floods or landslides are crossed. These alerts enable villagers to evacuate promptly and relocate to safer areas, thereby significantly improving emergency response times and minimizing risk to life and property. Furthermore, the RTDA

system enhances coordination between local authorities, emergency services, and communities by ensuring accurate and immediate communication during critical events. As noted in recent studies on disaster prediction and early warning technologies, such data-driven systems are crucial for effective disaster preparedness and response, particularly in regions with complex terrain and frequent weather-induced hazards.

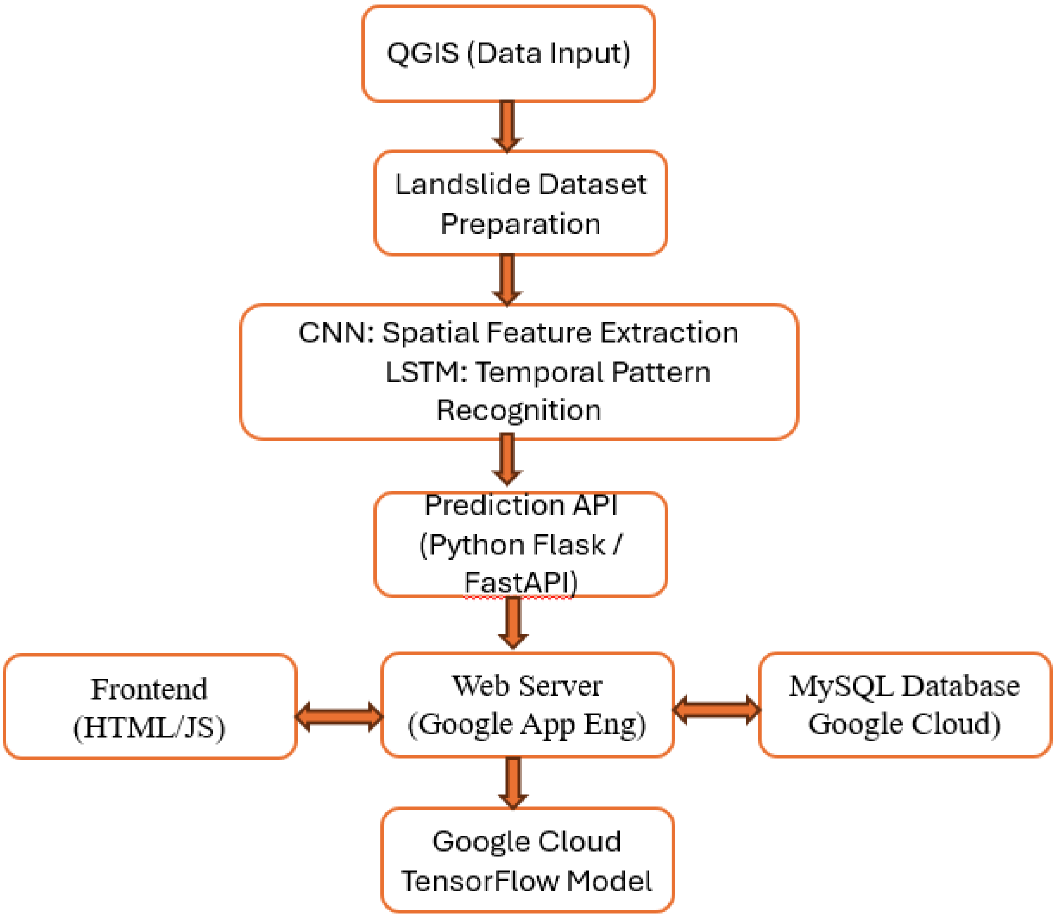
Proposed System:Landslides are among the most devastating natural hazards, particularly in regions with complex terrain, intense rainfall, and increasing human activity such as deforestation and unplanned urbanization. Effective prediction and early warning systems are crucial to mitigate their impact on human lives, infrastructure, and the environment. The proposed system aims to address this challenge by leveraging advanced geospatial data and artificial intelligence for real-time landslide-risk prediction.
As shown in figure 1 , system integrates geospatial mapping, deep learning, and cloud computing to build a robust and scalable landslide prediction framework. The process begins with the generation of a detailed landslide susceptibility dataset using Quantum GIS (QGIS), capturing both static and dynamic terrain features. A hybrid CNN-LSTM model is then developed—combining the spatial analysis capability of Convolutional Neural Networks (CNN) with the temporal forecasting strength of Long Short-Term Memory (LSTM) networks.

Figure 1. Proposed Architecture



To ensure accessibility and real-time usability, the model is integrated into a web-based platform developed using HTML, JavaScript, and MySQL, providing users with a responsive interface for predictions and alerts. The entire solution is deployed on Google Cloud Platform (GCP) for seamless scalability, high availability, and efficient resource management which is depicted in figure 2.
This innovative approach not only enhances prediction accuracy but also enables timely decision-making for disaster preparedness and risk mitigation in landslide-prone regions.

Figure 2.Flow diagram



Different steps performed in proposed architecture are explained as follows :

1. Data Generation and Preprocessing

The first phase involves generating and preprocessing geospatial data required for landslide-risk analysis. Quantum GIS (QGIS) software will be used to:

- Digitize landslide-prone areas.
- Extract key spatial parameters such as slope, elevation, land use, rainfall, drainage density, and vegetation index.
- Prepare a Landslide Susceptibility Dataset with both static (terrain-based) and dynamic (weather-based) features.
- Normalize and label the data into high-risk and low-risk zones.

2. Model Design: Hybrid CNN-LSTM

A hybrid deep learning model will be developed to improve prediction accuracy by combining spatial feature extraction (CNN) with temporal pattern learning (LSTM):

- CNN Component: Extracts spatial features from input maps and topographic imagery.
- LSTM Component: Learns temporal dependencies such as rainfall trends and seasonal patterns.
- Model Training: The dataset generated from QGIS will be used to train the hybrid model using Python and TensorFlow/Keras libraries. Hyperparameters will be optimized to enhance accuracy and generalization.

3. Web-Based Interface Development

A user-friendly landslide prediction web system will be developed using:

- Frontend: HTML, CSS, JavaScript for interactive UI.
- Backend: MySQL for storing user inputs, predicted results, and historical landslide records.
- Prediction API: The trained hybrid CNN-LSTM model will be hosted as a web service for real-time prediction queries.

4. Testing and Optimization

- The model will be tested using a hybrid approach, combining pretrained models with the LSTM architecture to:
  - Improve robustness on unseen data.
  - Enhance precision in spatial-temporal landslide forecasting.
- Performance metrics such as accuracy, precision, recall, and AUC will be evaluated.
- The web application will also be stress-tested for real-time performance and responsiveness.

5. Deployment on Google Cloud Platform (GCP)

- The complete system, including the trained model and web interface, will be deployed on Google Cloud Platform to ensure scalability, security, and 24/7 availability.
- Google App Engine will host the frontend, while Google Cloud Storage and SQL services will manage data and model storage.
- TensorFlow Serving on GCP will be used to expose the CNN-LSTM model as a REST API.

Benefits and challenges

1. Improved Prediction Accuracy;The hybrid CNN-LSTM model combines spatial analysis (via CNN) and temporal sequence learning (via LSTM), which results in more accurate and reliable landslide-risk predictions compared to traditional or standalone models.
2. Real-Time Monitoring and Alerts: Integrated with real-time environmental data (e.g., rainfall, slope, soil moisture), the system can provide early warnings to residents and authorities, enabling timely evacuation and disaster response.
3. Geospatial Intelligence :Using QGIS for data preparation allows detailed spatial mapping of high-risk zones. It helps authorities to prioritize infrastructure planning and risk mitigation in vulnerable areas.
4. Web-Based Accessibility : The system is built as a web application using HTML, JavaScript, and MySQL, making it easily accessible to disaster management teams, local governments, and the general public through any device with internet access.
5. Cloud Scalability: Deployment on Google Cloud Platform ensures high scalability, uptime, and performance. It allows the system to handle large datasets and real-time inference at scale without local infrastructure constraints.
6. Integration with Existing Disaster Systems: The model and interface can be integrated into existing state or national disaster management frameworks, enhancing current early warning capabilities.

Despite its potential, the proposed landslide prediction system faces several challenges that must be addressed for successful implementation and long-term sustainability. One of the primary concerns is the availability and quality of data. Accurate landslide prediction relies heavily on high-resolution, real-time geospatial and environmental data, which may be difficult to obtain consistently, especially in remote or forested regions. Incomplete or outdated data can significantly reduce the model's effectiveness. Additionally, the computational complexity of training and deploying a hybrid CNN-LSTM model presents a barrier, as such deep learning architectures require substantial processing power and memory, which may not be feasible without cloud support.

Another major challenge is model interpretability. While deep learning models can offer high accuracy, they often operate as black boxes, making it difficult for decision-makers to understand how specific predictions are generated. This can limit trust and acceptance, particularly in critical disaster management applications. Furthermore, the model may struggle to generalize across diverse geographic regions. A model trained on one area's data may not perform well in another due to varying geological, climatic, or land-use patterns, necessitating region-specific training and adaptation.

Maintenance and continuous updating of the system also pose challenges. To ensure accuracy over time, the model must be retrained regularly with new data, which requires ongoing technical expertise and resources. Lastly, the system's dependence on digital infrastructure and connectivity may limit its reach in rural or underdeveloped areas, where internet access is unreliable and digital literacy is low. Addressing these challenges is essential to fully realize the benefits of the proposed system in mitigating landslide risks.

Conclusion

This research presents a comprehensive, cloud-based solution for real-time landslide prediction by leveraging the combined strengths of geospatial data analysis and hybrid deep learning models. The use of QGIS enables the construction of detailed landslide susceptibility datasets, while the CNN-LSTM architecture effectively captures both spatial and temporal patterns inherent in landslide occurrences. The integration of this model into a web-based platform makes it accessible and user-friendly, while deployment on Google Cloud ensures scalability, high availability, and efficient performance. Despite challenges such as data quality, computational complexity, and generalization across regions, the system shows promising results in terms of accuracy and usability. It can serve as a valuable decision-support tool for local authorities, disaster management agencies, and community planners. Future work will focus on expanding datasets, improving model interpretability, and enhancing adaptability for broader geographic coverage. Overall, the proposed system marks a significant step toward proactive and intelligent landslide risk management using AI and cloud technologies.

References:

1. Praveen Kumar Rai , Kshitij Mohan, and V.K. Kumra, "Landslide Hazard and Its Mapping Using Remote Sensing and GIS", Journal of Scientific Research, Banaras Hindu University (Vol. 58, 2014)
2. Siti Nor Khuzaimah Binti Amit, Soma Shiraishi, Tetsuo Inoshita2, Yoshimitsu Aoki1, "Analysis of satellite images for disaster detection", Reserch Gate, 2018.
3. Naruephorn Tengtrairat , Wai Lok Woo 2 , Phetcharat Parathai , Chuchoke Aryupong ,Peerapong Jitsangiam and Damrongsak Rinchumphu, "Automated Landslide-Risk Prediction Using Web GIS and Machine Learning Models" Sensors, 2021.
4. Haojie Wang, Limin Zhang, Kesheng Yin, Hongyu Luo, and Jinhui Li, "Landslide Identification Using Machine Learning", ELSEVIER, 2020.
5. Bahareh Kalantar , Naonori Ueda, Vahideh Saeidi, Saeid Janizadeh, Fariborz Shabani, Kourosh Ahmadiand Farzin Shabani, "Deep Neural Network Utilizing Remote Sensing Datasets for Flood Hazard Susceptibility Mapping in Brisbane, Australia", remote sensing, 2021.
6. Yibing Xiong , Yi Zhou , Futao Wang , Shixin Wang, Jingming Wang, Jianwan Ji , and Zhenqing Wang, "Landslide Susceptibility Mapping Using Ant Colony Optimization Strategy and Deep Belief Network in Jiuzhaigou Region", IEEE, 2021.

7. Viet-Ha Nhu, Ayub Mohammadi, and Himan Shahabi, "Landslide Susceptibility Mapping Using Machine Learning Algorithms and Remote Sensing Data in a Tropical Environment", International Journal of Environmental Research and Public Health, 2020
8. R Archana Reddy, R Gobinath, Chilupuri Saloni Khanna, G.Shyamala, “Machine Learning-Based Landslide Prediction System for Hilly Areas”, IOP Publishing, 2020
9. Naruephorn Tengtrairat, Wai Lok Woo, Phetcharat Parathai, Chuchoke Aryupong, Peerapong Jitsangiam, Damrongsak Rinchumphu, “ Automated Landslide-Risk Prediction Using Web GIS and Machine Learning Models", Sensors, 2021.
10. Kounghoon Nam, and Fawu Wang, “An extreme rainfall-induced landslide susceptibility assessment usingautoencoder combined with random forest in Shimane Prefecture, Japan”, SpringerOpen ,Geoenvironmental Disasters, 2020.
11. Tingyu Zhang, Yanan Li, Tao Wang, Huanyuan Wang, Tianqing Chen, Zenghui Sun, Dan Luo, Chao Li and Ling Han, “Evaluation of diferent machine learning models and novel deep learning-based algorithm for landslide susceptibility mapping”, GeoScience Letters,2022.
12. Z. Zhu, L. Song, Y. Zhou, and T. Liu, "Landslide Susceptibility Prediction Modeling Based on Self-Screening Deep Learning Model," arXiv preprint, arXiv:2304.06054, 2023. [Online]. Available: https://arxiv.org/abs/2304.06054
13. T. Ganerød, M. Hov, and S. Nordbotten, "Automating Global Landslide Detection with Heterogeneous Ensemble Deep-Learning Classification," arXiv preprint, arXiv:2310.05959, 2023. [Online]. Available: https://arxiv.org/abs/2310.05959
14. Y. Liu, H. Wang, J. Zhang, and C. Wang, "Monitoring and Prediction of Landslide-Related Deformation Based on GCN-LSTM and SAR Imagery," Natural Hazards, vol. 117, 2023. [Online]. Available: https://link.springer.com/article/10.1007/s11069-023-06121-8
15. N. Le, S. Hoa, and M. Nguyen, "Landslide Detection and Segmentation Using Remote Sensing Images and Deep Neural Network," arXiv preprint, arXiv:2312.16717, 2023. [Online]. Available: https://arxiv.org/abs/2312.16717
16. A. Abujayyab, "Enhanced Landslide Susceptibility Prediction with 3D ALOS PALSAR Imagery and Neural Networks," International Journal of Geography and Geography Education (IGGE), vol. 49, pp. 1–18, 2024. [Online]. Available: https://dergipark.org.tr/en/pub/igge/issue/82882/1380504
17. D. Anil and S. H. Manjula, “High-Precision Landslide Susceptibility Mapping Using CNN-LSTM-Attention Models,” *Engineering, Technology & Applied Science Research*, vol. 15, no. 4, pp. 25486–25491, Aug. 2025.
18. X. Yuan et al.**,** “CNN-LSTM, CNN-SRU, CNN-GRU Models for Landslide Susceptibility: A Case Study in Guizhou, China,” *Remote Sens.*, vol. 16, no. 8, art. 1344, Apr. 2024.
19. H. Yang *et al.*, “Improved Landslide Deformation Prediction Using Convolutional Neural Network–Gated Recurrent Unit and Spatial–Temporal Data,” *Remote Sens.*, vol. 17, no. 4, art. 727, Feb. 2025.
20. Q. Xu, C. Ouyang, T. Jiang, X. Fan, and D. Cheng, “DFPENet-geology: A Deep Learning Framework for High Precision Recognition and Segmentation of Co-seismic Landslides,” *arXiv preprint arXiv:1908.10907*, 2019.
21. L. Le ***et al.***, “Machine Learning for High-Resolution Landslide Susceptibility Mapping: Case Study in Inje County, South Korea,” *Front. Earth Sci.*, vol. 11, art. 1268501, Sept. 2023.