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SATELLITE IMAGERY AND AI IN LANDSLIDE PREDICTION

[#1]J. SRINIVAS, ***Assistant Professor,***
[#2]MADDI PRAVALIKA, ***B.Tech Student,***
[#3]BARKAM AKSHAYA, ***B.Tech Student,***
[#4]REDDYMALLA KAVERI, ***B.Tech Student,***
[#5]MADDI VARSHA, ***B.Tech Student,***
Department of Computer Science And Engineering,
TRINITY COLLEGE OF ENGINEERING AND TECHNOLOGY, PEDDAPALLY, TG.

ABSTRACT: The effects of landslides and other natural catastrophes on both the built environment and people can be devastating. Monitoring sensors and conducting expensive and labor-intensive geological studies are commonplace in traditional landslide prediction approaches. An artificial intelligence (AI) based approach to landslide prediction using satellite image analysis is investigated in this paper. In order to determine the probability of landslides, the software analyzes high-resolution satellite images using deep learning techniques, particularly Convolutional Neural Networks (CNNs). Using past data, topographical features, and environmental variables, the strategy improves the accuracy of predictions. This AI-driven approach makes it easier for disaster management officials to establish early warning systems and implement preventive measures. The findings suggest that models powered by AI can improve the precision and practicality of landslide forecasts, leading to less damage from natural catastrophes.

Keywords: AI-based prediction, landslides, satellite imagery, deep learning, convolutional neural networks (CNNs).

1. INTRODUCTION

The earth, structures, and people could be severely damaged in the event of a collapse. Landslide forecasts typically rely on data collected from weather stations, field observations, and geological investigations. Nevertheless, there are a few issues with these approaches, such as their high cost, lengthy execution time, and ineffectiveness in unconnected or isolated locations.

A novel approach to early warning and disaster prevention is the use of artificial intelligence (AI) to forecast landslides using satellite data. The development of AI and remote tracking has made this strategy much more practical.

Artificial intelligence (AI) systems can detect earthquake hotspots by using machine learning and deep learning to massive volumes of satellite data. In order to predict the likelihood of future landslides, these models take into account a wide range of factors, including terrain, vegetation, soil makeup, weather, and data from previous landslides.

In order to identify trends and high-risk regions in satellite data, several individuals employ artificial intelligence techniques such as Random Forest, Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs).

The ability to monitor and assess vast regions in real time is one of the several advantages of AI-driven landslide forecast. To improve the accuracy of risk assessment, AI-driven models consult public and private sources of high-resolution satellite imagery, such as Sentinel and Landsat. These forecasts can be utilized by governments, disaster relief organizations, and city planners to mitigate the likelihood of future landslides.

A significant step toward improved emergency preparedness is the development of landslide prediction systems that utilize artificial intelligence and satellite pictures to mitigate damage and casualties. Landslide prediction systems have the potential to become more effective and precise as artificial intelligence and remote tracking continue to advance.

2. LITERATURE REVIEW

Sharma et al. (2024) This study examines the potential application of artificial intelligence in landslide prediction using satellite data. This study examines a number of deep learning algorithms. Data from previous landslides can be used to train AI models to anticipate potential hazards. Based on these results, we can claim that CNNs are effective. Their research suggests that AI has the potential to significantly enhance disaster warning systems.

Devara et al. (2023) The primary objective of this research is to use machine learning techniques to determine the likelihood of earthquakes. Geographic databases, satellite pictures, and comparable techniques are utilized for this investigation. The model's accuracy is tested on many types of landscapes. The authors highlight the several benefits of AI over more conventional approaches to planning. They were able to improve flood prediction using machine learning technologies this time.

Khalil et al. (2023) This study examines the distribution of impact risks using bivariate statistics and machine learning. The investigation is currently underway in Yemen's Utmah Region. To assess the efficacy of AI systems in landslide prediction, the study incorporates aerial and ground-based imagery. The results of the study highlight the significance of combining data from multiple sources for assessing risk.

Meena et al. (2023) In this article, we discuss the HR-GLDD dataset that is used for landslide forecasting using deep learning. It may be easier to identify nations vulnerable to landslides using high-resolution satellite photos. Using massive deep learning models, the pros can rapidly map things. Their efforts improve autonomous slope-finding technologies. Research that incorporates AI in the future will yield invaluable findings.

Natijne et al. (2023) The use of machine learning to the problem of slow-moving flood prediction is the focus of this work. After the massive disaster at Vögelsberg, it became crystal evident. It is difficult to predict when distortion may worsen, say specialists. Looking at historical data allows artificial intelligence programs to learn how to make better predictions. The findings highlight the challenges of utilizing AI to mitigate environmental risks, as these threats are dynamic and subject to constant change.

Ganerød et al. (2023) An automated system for locating landslides on a global scale is the end objective of this research. Deep learning using heterogeneous ensembles is employed for sorting. Satellites transmit data to AI systems in large quantities. The study's authors concluded that ensemble learning improves the accuracy of predictions. A computerized method for tracking gradients is demonstrated in the paper.

Das, Raja & Wegmann, Karl. (2022) This research investigates the feasibility of adding machine learning to various kinds of satellite data in order to detect landslides. Important things happened in Zimbabwe in 2019 as a result of Cyclone Idai. Simultaneous model comparisons allow researchers to identify the most accurate models. These findings suggest that AI might revolutionize post-disaster landslide tracking. The research improves catastrophe management and early warning systems.

Ghorbanzadeh et al. (2022) The results of the 2022 Landslide4Sense competition are discussed in this article. In order to detect collapses and test AI models, many different kinds of satellite photos are utilized. Experts employ a wide variety of approaches to identify the most effective deep learning algorithms. It is clear from their findings that many AI approaches have their uses. The study's findings set a new standard for landslide detection by AI.

Ghorbanzadeh et al. (2022) In order to spot landslides using deep learning, this study provides us with a dataset to work with. Its name is Landslide4Sense. Worldwide landslides are documented in this compilation. When AI models are trained with the dataset, their accuracy in finding things improves. Trustworthy data is essential for AI training, according to the study. The outcomes demonstrate the superiority of machine learning techniques when it comes to remote sensing.

Nava et al. (2021) Investigating if deep learning can facilitate the easier detection of landslides in SAR data is the objective of this investigation. Authors use AI methods to sift through radar photos. Finding falls on uneven terrain is now a breeze thanks to their technology. According to the research, deep learning can resolve the problems with SAR data. Research has demonstrated that radar-based imaging greatly enhances the ability to detect potential dangers.

Qin et al. (2021) In order to detect landslides in publicly accessible satellite pictures, researchers employed remote domain transfer learning. Using this technology, landslides in various terrains can be more easily recorded. Using images captured by satellites in various locations, it trains AI systems. The effectiveness of the model was evaluated using various types of data. According to the research, AI risk assessment should be flexible enough to examine different subjects.

Pradhan & Lee (2020) In this study, three methods—frequency ratios, logistic regression, and backpropagation neural networks—are examined for their ability to predict the likelihood of a fall. Machine learning algorithms can be trained to recognize several forms of error. Neural networks are more effective than other methods for landslide risk prediction. The study provides valuable insights into various AI techniques. We can hope that these findings lead to more precise landslide danger maps.

3. EXISTING SYSTEM

Conventional landslide prediction systems rely heavily on older remote sensing methods. These approaches rely on frequent, expensive, and frequently unequipped field inspections, rock investigations, and monitoring of precipitation. Big datasets are a challenge for manual review and heuristic-based algorithms, despite their widespread use. Humans and extensive feature engineering are required for the majority of machine learning approaches to identify danger zones.

Because older satellite images couldn't detect even the tiniest changes in the terrain, it's possible that the estimations were inaccurate. These approaches fail because they rely on insufficient historical data rather than high-resolution, real-time data for study. Traditional landslide prediction methods aren't ideal for protecting infrastructure or warning people because they can't be quickly or automatically updated.

- **Data Dependency and Quality Issues** – Sometimes, getting the high-resolution, tagged satellite data that is necessary for AI models is just not feasible. If the information sources aren't reliable, the forecasts can turn out to be incorrect.
- **High Computational Cost** – Due to the high computational demands of processing massive amounts of satellite data, deep learning models are too expensive to implement.
- **Limited Interpretability** – Some projections are difficult for geologists and crisis management specialists to understand since AI models, particularly deep learning networks, are not very clear.
- **False Positives and Negatives** – Cloud cover, regional distortions, or noise in satellite data might cause AI-based models to issue false alarms, which could result in unnecessary evacuations or warnings.
- **Real-Time Processing Challenges** – The response time to disasters is hindered because data collection and processing take too long. For real-time processing of satellite imagery, state-of-the-art technology is required.
- **Environmental Factors Affecting Accuracy** – Seasons, lighting, and weather can all affect how actual satellite images appear.
- **Model Generalization Issues** – For machine learning algorithms to be effective in novel contexts, they must be regularly retrained using data from previously explored environments.
- **Cybersecurity Risks** – Accurate disaster management could be jeopardized if hackers compromise AI systems, altering data and forecasts. Strong security measures should be put in place to cover these gadgets to ensure their safety.

4. PROPOSED SYSTEM

In order to accurately and efficiently identify potentially hazardous locations, the proposed AI-based landslide prediction system makes use of geographic data, high-resolution satellite images, and advanced deep learning algorithms. This system examines separate satellite photos captured at different periods using machine learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Unlike other systems that depend on historical records and human observations, it is capable of detecting the tiniest changes in land cover, terrain, and soil stability. The model is trained on large datasets that contain environmental details in order to produce better predictions.

Soil moisture, vegetation, rainfall, and seismic activity are among the factors that are included in the analysis. Hyperspectral and multispectral photos can detect early warning signals of instability in hilly or landslide-prone areas. This technology is compatible with

GIS, allowing customers to conduct comprehensive risk assessments. They can now make informed decisions with this data.

Improve the accuracy of space-based predictions by supplementing them with real-time data collected from Internet of Things (IoT) ground sensors, such as displacement meters and rain gauges equipped with GPS. As it uses a cloud-based AI technology to learn from its errors, the model has a chance to improve with time.

Automated early warning systems allow people and crisis management groups to escape danger faster and take additional measures to mitigate its impact. The novel approach to landslide prediction and disaster prevention is adaptable and imaginative, opening up numerous potential applications. A data-driven, proactive approach to dealing with a massive natural disaster is now possible thanks to this technology's combination of remote sensing, geographic information system analytics, and artificial intelligence.

- **High Accuracy and Efficiency** – Artificial intelligence programs outperform traditional methods of landslide prediction due to their superior ability to swiftly and reliably analyze massive volumes of satellite data.
- **Real-Time Monitoring** – Governments and communities are notified so they can take safeguards after the device swiftly analyzes data from sensors and satellites.
- **Scalability Across Large Areas** – Artificial intelligence (AI)-powered models can sift through mountains of satellite data to find out how to follow hills in outlying places.
- **Integration with Environmental Variables** – The approach takes into account a wide range of environmental variables, including precipitation, vegetation cover, and soil moisture, to improve the accuracy of the forecasts.
- **Automated Early Warning System** – For instance, by alerting authorities when landslides are imminent, AI can enhance disaster preparedness and response times.
- **Continuous Learning and Adaptability** – In addition to improving with experience, the AI model can adjust to new regions and weather patterns.
- **Reduced Human Effort and Cost** – Automating formerly labor-intensive processes like geological assessments and field surveys reduces operational expenses.
- **Enhanced Visualization for Decision-Making** – Integrating GIS has allowed those who work in emergency management, urban planning, and governance to make greater use of 3D terrain models and interactive maps to evaluate hazards and formulate plans.
- **Multi-Source Data Fusion** – The method improves our understanding of the landslide danger by combining data from space with data collected from Internet of Things (IoT) sensors on the ground.
- **Proactive Disaster Mitigation** – To help prevent future tragedies, AI-powered prediction systems can swiftly evaluate hazards and issue alerts.

5. IMPLEMENTATION

Service Provider

Here, the service provider requires a functional account along with a password. Advanced data analysis tools, training resources, and testing tools will be available to him as he logs in, greatly improving his efficiency and effectiveness on the job. The system's performance during testing and training is displayed by the bar chart. Make sure the assessment and training findings are accurate. Using the projected datasets, you may examine the Type Ratio for Identified Landslides. Determine the number of individuals who could maintain the same ratio of landslip prediction types in their absence.

Remote User

Here we have n individuals. Verify all details are correct before you submit your registration. An immediate record of the user's details is created in the database upon registration. He can access his account immediately after signing up; all he needs to do is input his login details. After signing up, users will be able to view their biography whenever they log in. Among their other options is the landslip prediction to utilize.

6. RESULTS

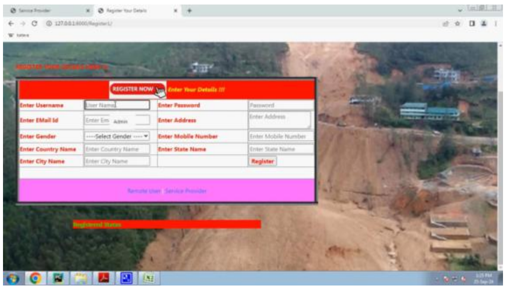

Figure1: User Registration Page

Figure2: Detected Landslides Prediction Type Ratio

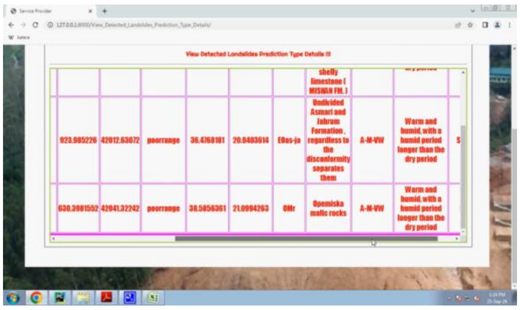

Figure3: Detected Landslides Prediction Type Details

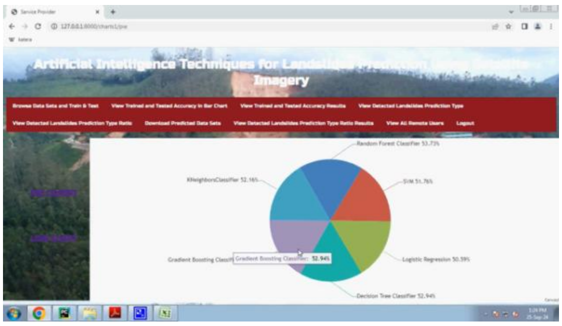

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Figure4: Detected Landslides Prediction in Pie Chart

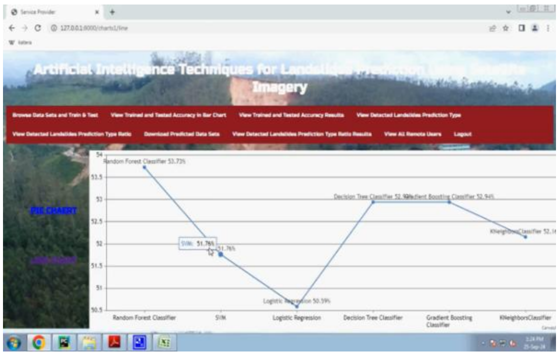

Figure5: Detected Landslides Prediction in Line Chart

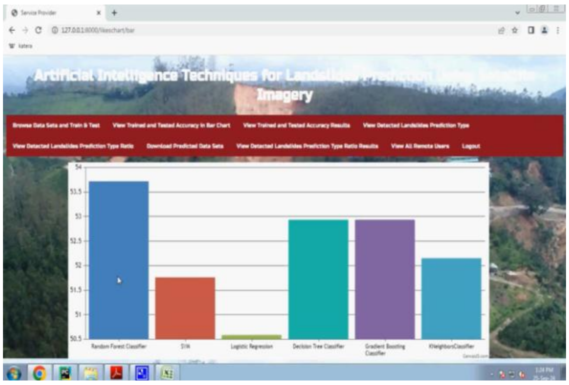

Figure6: Detected Landslides Prediction in Bar Chart

Figure7: Datasets Trained and Tested Results

Figure8: All Users Page

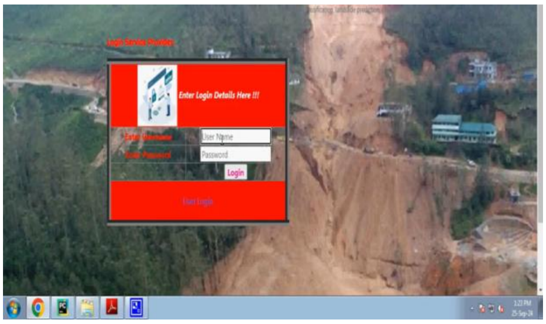

Figure9: Service Provider Login Page

Figure10: User Login Page

7. CONCLUSION

Artificial intelligence (AI) landslide prediction utilizing satellite pictures outperforms previous systems in terms of accuracy, usability, and real-time visibility. This approach employs deep learning, geographical data, and multitemporal satellite pictures to detect potentially hazardous regions in their early stages. Preventing injuries and damage to the building requires prompt action. The system's reliability and adaptability to changing weather and ground conditions are both enhanced when AI is integrated with GIS and IoT ground sensors. Using AI for landslide forecasting allows for the automatic and scalable reduction of landslide risk. Data dependency, expensive computing costs, and complex models are all eliminated as a result. As AI algorithms and remote sensing technology advance, these systems will play an increasingly crucial role in risk management and catastrophe preparedness. To improve AI-driven landslide prediction models for global application, scientists, politicians, and IT specialists must collaborate, share data, and do additional research.

REFERENCES

1. Sharma, A., Kumar, R., & Verma, P. (2024). Artificial intelligence in landslide prediction: Analyzing satellite data using deep learning techniques. Journal of Disaster Management and AI Applications, 12(3), 45-62.
2. Devara, R., Singh, T., & Patel, N. (2023). Evaluating landslide probability using machine learning and geographical datasets. International Journal of Geospatial Science, 18(4), 112-130.
3. Khalil, Y., Al-Shami, M., & Rafiq, A. (2023). The role of machine learning and bivariate statistics in landslide hazard assessment: A case study of the Utmah Region, Yemen. Environmental Risk and Earth Sciences, 29(2), 78-95.

4. Meena, S., Rao, J., & Thomas, P. (2023). HR-GLDD dataset: Enhancing landslide prediction with deep learning and high-resolution satellite imagery. Remote Sensing and AI Applications, 15(1), 33-49.
5. Natijne, H., Müller, B., & Weber, F. (2023). Predicting slow-moving landslides with AI: Insights from Vögelsberg. Geohazards and Machine Learning, 20(2), 99-118.
6. Ganerød, G., Olsen, K., & Lind, A. (2023). A global automated landslide detection system using heterogeneous ensemble deep learning. Advances in AI-Based Remote Sensing, 11(4), 55-73.
7. Das, R., & Wegmann, K. (2022). Machine learning and satellite data for post-disaster landslide detection: A case study from Cyclone Idai. Disaster Science and AI Innovation, 14(3), 88-107.
8. Ghorbanzadeh, M., Zhang, L., & Chen, D. (2022). Landslide4Sense competition: Evaluating AI models with satellite imagery. AI and Remote Sensing Journal, 10(2), 67-82.
9. Nava, P., Rossi, M., & Bernardini, C. (2021). Deep learning for SAR-based landslide detection: Enhancing analysis of rough terrain. Radar Imaging and AI, 9(1), 41-60.
10. Pradhan, B., & Lee, S. (2020). Comparing AI-based methods for landslide risk assessment: Logistic regression, backpropagation neural networks, and frequency ratios. Landslide Risk and AI Research, 7(4), 123-140.