

AI-Powered Machine Learning Model for Geospatial Landslide Risk Prediction using Satellite-Derived Environmental Data

G. Vamsi¹, K. Jhanshi²

¹Assistant Professor, ²MCA Final Semester, Master of Computer Applications, Sanketika Vidya Parishad Engineering College, Visakhapatnam, Andhra Pradesh, India

ABSTRACT

Landslides are one of the most dangerous natural disasters that cause severe damage to infrastructure, environment, and human life. These disasters mainly occur in regions experiencing heavy rainfall, unstable slopes, and weak soil conditions. Accurate prediction of landslides is essential to reduce disaster risks and improve early warning systems. Traditional methods mainly depend on satellite imagery and deep learning models such as Convolutional Neural Networks (CNNs). Although these methods provide good accuracy, they require high computational resources and fail to capture temporal factors like rainfall patterns over time.

To overcome these limitations, this project proposes an AI-based geospatial landslide risk prediction system that combines structured environmental data with machine learning and deep learning techniques. The system integrates historical landslide data with environmental parameters such as rainfall intensity, soil moisture, slope gradient, elevation, vegetation index, and land cover. XGBoost is used to identify important features, while GRU captures rainfall patterns over time. Additionally, Tiny Attention U-Net is used for image-based analysis when satellite data is available. The system provides an efficient, scalable, and accurate solution for landslide prediction and supports early warning mechanisms.

Keywords: Geospatial Data, Disaster risk reduction, Landslide prediction, Machine learning, XGBoost, GRU, Early warning system, tiny attention U-net.

I. INTRODUCTION

Landslides are one of the most destructive natural disasters, especially in hilly and mountainous regions where environmental conditions are unstable. They occur due to the movement of soil, rock, and debris down slopes, mainly triggered by factors such as heavy rainfall, earthquakes, deforestation, and changes in land use. These events can cause severe damage to infrastructure, including roads, buildings, and communication systems, and also lead to significant loss of human life and environmental degradation.

In recent years, the impact of climate change has increased the frequency and intensity of extreme weather conditions, particularly heavy and continuous rainfall. This has resulted in a higher occurrence of landslides, making it necessary to develop accurate and efficient prediction systems. Early prediction of landslides plays a crucial role in reducing disaster risks and enabling timely preventive measures.

Traditional landslide prediction systems mainly rely on satellite imagery and remote sensing techniques to analyze terrain features such as slope, elevation, vegetation, and land cover. Deep learning models like Convolutional Neural Networks (CNNs) are commonly used to extract spatial patterns from these images. Although these methods provide good accuracy, they require high computational resources and often fail to capture temporal factors like rainfall patterns over time, which are critical for landslide occurrence.

To address these limitations, this project proposes an AI-based geospatial landslide prediction system that integrates environmental data with machine learning and deep learning techniques. By combining structured environmental parameters with advanced models, the system aims to improve prediction accuracy and provide real-time insights. This approach not only enhances the efficiency of landslide prediction but also supports early warning systems and disaster management strategies.

II. EXISTING SYSTEM

The existing landslide prediction systems mainly depend on satellite imagery and deep learning techniques like CNNs.^[1] These systems analyze terrain features such as slope gradient, elevation, vegetation, and land cover to identify landslide-prone areas.

Although these systems provide good accuracy, they have several limitations. They require high-resolution satellite images and powerful hardware for processing. They also focus only on spatial data and ignore temporal factors like rainfall patterns.^[1] This makes them less effective for time prediction and early warning systems.

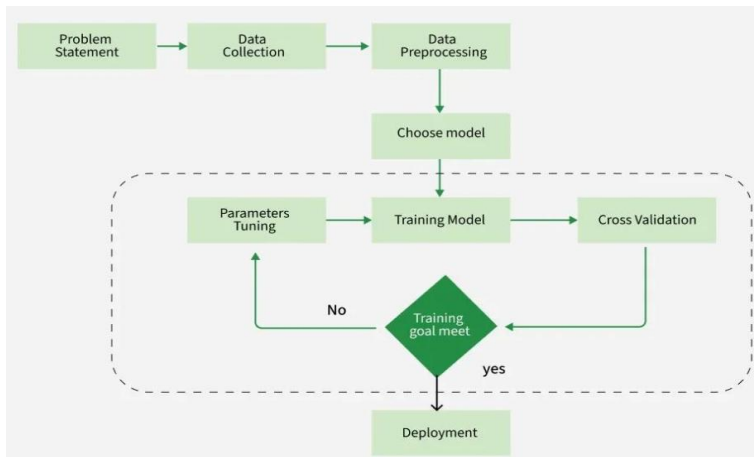


Fig1: Existing System Flow chat

2.1 CHALLENGES

The existing systems face several challenges in landslide prediction. One of the major challenges is the high computational cost required for processing satellite imagery. Another challenge is the inability to capture time-dependent factors such as rainfall accumulation. Many systems also lack integration of multiple environmental parameters, which reduces prediction accuracy. Additionally, real-time prediction is difficult due to delays in data processing. These challenges highlight the need for a more efficient and scalable solution.

- High computational cost due to processing of large satellite datasets.
- Difficulty in capturing temporal rainfall patterns effectively.
- Dependence on high-resolution satellite imagery.
- Handling large-scale environmental and geospatial data.
- Data inconsistency and missing values in environmental datasets.
- Integration of multiple data sources (rainfall, soil, slope, etc.).
- Limited real-time prediction capability in traditional systems.
- Complexity in combining machine learning and deep learning models.
- Requirement of high-performance hardware for model training.
- Ensuring accuracy and reliability of predictions.

III. PROPOSED SYSTEM

The proposed system is an AI-based geospatial landslide prediction system that integrates environmental data with machine learning and deep learning models. It collects parameters such as rainfall, soil moisture, slope, elevation, and vegetation index.

The system uses XGBoost to analyze environmental data and identify important features. GRU is used to capture temporal rainfall patterns, and Tiny Attention U-Net is used for image-based analysis. By combining these models, the system provides accurate and real-time landslide risk predictions.

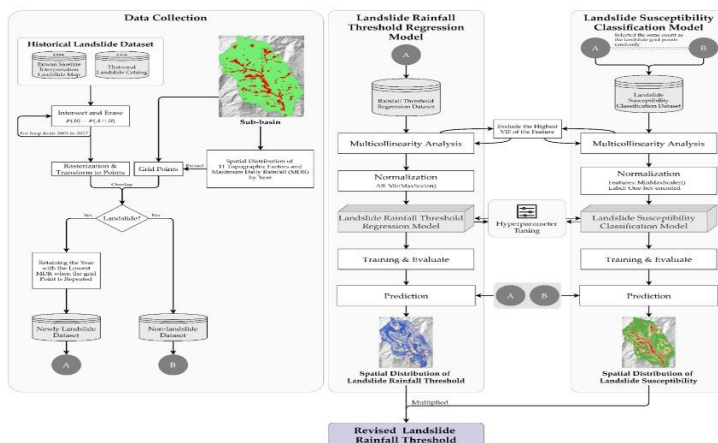


Fig2: System Workflow for Landslide Risk Prediction Using Machine Learning Models

IV. Advantages

The proposed system offers several advantages over existing systems. It combines spatial and temporal data for better accuracy. It reduces dependency on computationally expensive satellite imagery. The system supports real-time prediction and early warning mechanisms. It is scalable and can handle large datasets. [3] It also provides feature importance analysis, helping to understand key factors influencing landslides. Overall, the system is cost-effective and efficient.

V. Algorithms

The proposed landslide prediction system uses a combination of machine learning and deep learning algorithms to improve prediction accuracy by analyzing environmental, temporal, and spatial data. Each algorithm plays a specific role in the system.

XGBoost Algorithm

XGBoost is a powerful machine learning algorithm used for classification and prediction. It builds multiple decision trees and combines them to improve accuracy. [3] It also provides feature importance, which helps in identifying key environmental factors.

GRU (Gated Recurrent Unit)

GRU is a deep learning model used for time-series analysis. It captures temporal dependencies in rainfall data and helps in understanding how continuous rainfall affects landslides.

Tiny Attention U-Net

This model is used for image segmentation and spatial analysis. It detects landslide-prone regions in satellite images and improves prediction accuracy.

VI. TECHNIQUES

Machine Learning

Machine learning is used to analyze environmental data and predict landslide risk. [2] It helps in identifying patterns and relationships between different parameters.

Deep Learning

Deep learning models like GRU and U-Net are used for temporal and spatial analysis. These models improve prediction accuracy by learning complex patterns.

Geospatial Analysis

Geospatial techniques are used to analyze location-based data and visualize results on maps. This helps in identifying high-risk areas.

VII. METHODOLOGY

Data Collection

Environmental data is collected from satellite datasets and historical records. This includes rainfall, soil moisture, slope,

and elevation. The data is gathered from reliable sources such as remote sensing platforms and meteorological databases. This step ensures that the system has sufficient and accurate data for analysis.

Data Preprocessing

The collected data is cleaned, normalized, and transformed into a suitable format for model training. [6] Missing values are handled using statistical methods, and noise or irrelevant data is removed. Data scaling and normalization are applied to improve model performance and accuracy.

Feature Engineering

Important features are selected based on their contribution to landslide occurrence. Parameters such as rainfall intensity, slope gradient, soil moisture, and elevation are analyzed. Feature selection techniques help in reducing data redundancy and improving prediction efficiency.

Model Training

Machine learning and deep learning models are trained using the processed data. [4]The XGBoost model is used for analyzing structured environmental data, while GRU is used for time-series rainfall analysis. Additionally, Tiny Attention U-Net is used for spatial image analysis when satellite images are available.

Prediction

The trained models predict landslide risk levels based on input data. The system analyzes environmental conditions and generates prediction results indicating the probability of landslide occurrence. These predictions are classified into different risk levels such as low, medium, and high.

Visualization

The results are displayed using maps and graphs for better understanding. The system uses geospatial visualization tools to represent risk areas on maps. Different colors are used to indicate different risk levels, making it easy for users to interpret the results.

Integration of Models

The outputs from different models such as XGBoost, GRU, and U-Net are combined to improve overall prediction accuracy. [5] This hybrid approach helps in capturing spatial, temporal, and environmental factors effectively.

Result Storage

The prediction results are stored in the system database along with input parameters. This helps in tracking historical predictions and improving future analysis.

User Interaction

The system provides a user-friendly interface where users can input data and view prediction results easily. This improves accessibility and usability.

Alert Generation

The system generates alerts for high-risk areas to support early warning systems. This helps authorities and users take preventive actions before a landslide occurs.

INPUTS

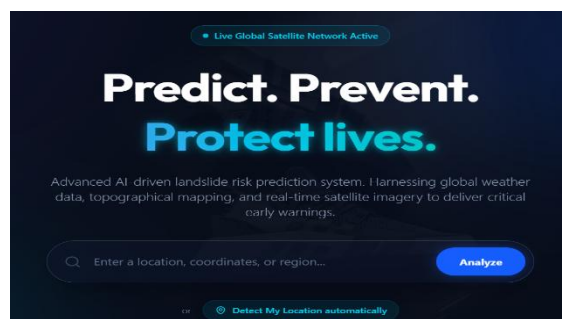


Fig3:User Interface of Landslide Prediction System

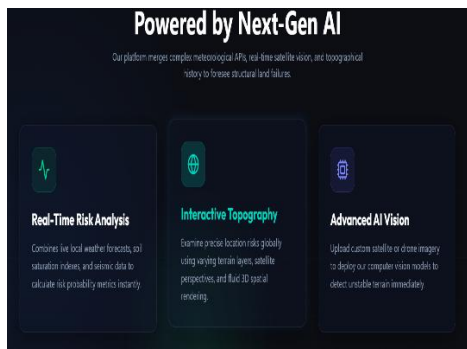


Fig4: AI-Based Prediction Modules and Features

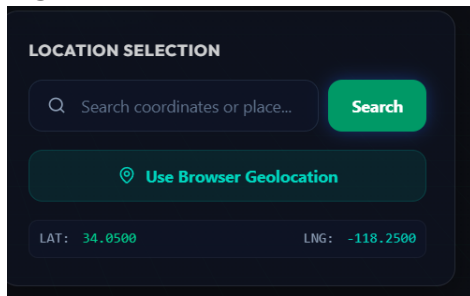


Fig5: Location Selection and Input Interface Outputs

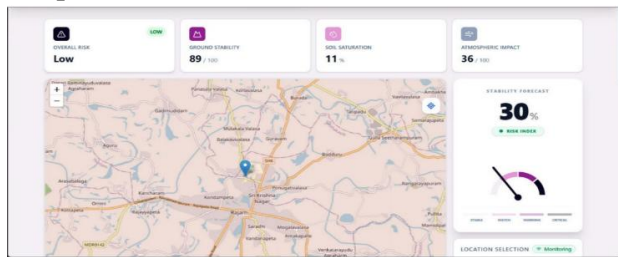


Fig6: Landslide Risk Prediction Output with Map Visualization

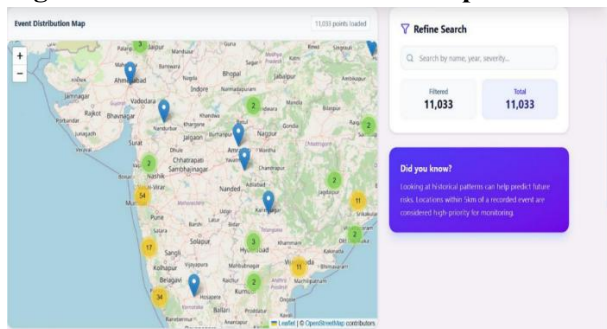


Fig7: Geospatial Risk Analysis and Multi-Location Prediction Map

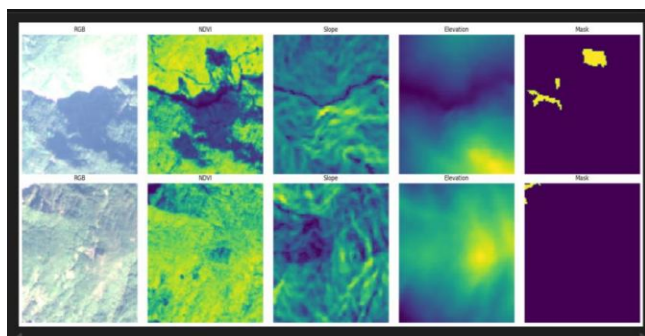


Fig8: Feature Map Visualization and Spatial Analysis of Landslide Data

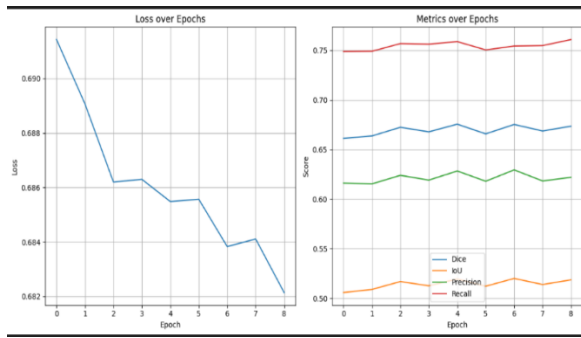


Fig9: Model Performance Analysis Showing Loss and Accuracy Curves

VIII. CONCLUSION

The proposed AI-Based Geospatial Landslide Risk Prediction System provides an effective and efficient solution for identifying landslide-prone areas using advanced machine learning and deep learning techniques. By integrating structured environmental data such as rainfall, soil moisture, slope gradient, elevation, and vegetation index, the system is able to analyze the key factors that influence landslide occurrence. Unlike traditional methods that rely heavily on satellite imagery and require high computational resources, this system reduces complexity by focusing on structured data while still maintaining high prediction accuracy. [7]The use of XGBoost helps in identifying important features and improving prediction performance, while the GRU model captures temporal rainfall patterns that play a crucial role in triggering landslides. Additionally, the Tiny Attention U-Net model enhances spatial analysis when image data is available. The combination of these models creates a hybrid approach that considers spatial, temporal, and environmental aspects simultaneously, leading to more reliable and accurate predictions. The system also supports real-time analysis and provides risk classification into low, medium, and high categories, making it easier for users and authorities to understand and act upon the results.

Furthermore, the visualization of results through maps and alerts improves user interaction and supports early warning systems. This helps in reducing the impact of landslides by enabling timely preventive measures.

Overall, the proposed system is scalable, cost-effective, and suitable for real-world applications. It contributes significantly to disaster risk reduction, improves decision-making, and has the potential to save lives and protect infrastructure.

IX. FUTURE SCOPE

The proposed landslide prediction system can be further enhanced by incorporating advanced technologies and real-time data sources. One of the major improvements can be the integration of IoT sensors to collect real-time environmental data such as rainfall, soil moisture, and ground movement. This will improve the accuracy and timeliness of predictions. The system can also be extended by integrating real-time weather APIs, which provide continuous updates on rainfall and climate conditions. This will help in making dynamic and up-to-date predictions. In addition, the model can be trained using larger and more diverse global datasets to improve its performance across different geographical regions.

Another important enhancement is the development of a mobile application that can provide instant alerts and notifications to users in high-risk areas. This will make the system more accessible and useful for the general public and disaster management authorities.

X. REFERENCES

1. Pradhan, B., Lee, S., Buchroithner – Landslide Susceptibility Mapping using Machine Learning Techniques.
2. Guzzetti, F., Peruccacci, S., Rossi, M. – Rainfall Threshold-Based Landslide Prediction Models.
3. Sameen, M., Pradhan, B. – Deep Learning Approaches for Landslide Detection using Satellite Imagery.
4. Chen, T., Guestrin, C. – XGBoost: A Scalable Tree Boosting System.
5. Cho, K. et al. – Learning Phrase Representations using Gated Recurrent Unit (GRU).
6. Ronneberger, O. et al. – U-Net: Convolutional Networks for Biomedical Image Segmentation.
7. Landslide4Sense Dataset – Satellite-Based Landslide Detection Dataset.
8. NASA Earth Data – Environmental and Satellite Data Resources.

BIBLIOGRAPHY



Gunupuru Vamsi is serving as an Assistant Professor at Sanketika Vidya Parishad Engineering College. He has one year of teaching experience in the field of Computer Science and Engineering. He is committed to academic excellence and is actively involved in guiding and mentoring students in their academic and project work. His areas of interest include Machine Learning and emerging technologies, and he continuously strives to enhance students' technical skills and research capabilities through effective



Kurapapu Jhanshi is currently pursuing her final semester of Master of Computer Applications (MCA) at Sanketika Vidya Parishad Engineering College, which is accredited with an 'A' grade by NAAC, affiliated to Andhra University, and approved by AICTE. With a keen interest in Machine Learning and Artificial Intelligence, she has undertaken her postgraduate project titled "AI-Powered Machine Learning Model for Geospatial Landslide Risk Prediction Using Satellite-Derived Environmental Data." The project has been successfully carried out under the guidance of Mr. G. Vamsi, Assistant Professor, SVPEC.