International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 11, pp 154-159, November-2023

https://doi.org/10.47001/IRJIET/2023.711022

Pre-Disaster and Risk Detection Using AI Prediction System

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Abstract **- Residents of Ratnapura District's communities are seriously at risk from landslides. The creation of precise and timely landslide prediction systems is essential to reduce the risks and improve readiness for disasters. Landslide prediction in the Ratnapura District is the topic of a larger Pre-Disaster and Risk Detection AI Prediction System presented in this paper. The component seeks to offer the likelihood of possible landslides by utilizing cutting-edge machine learning techniques and geographical data. To build a complete landslide prediction model, the suggested system combines topographical and geological data sources. The system examines the correlations between numerous environmental parameters using machine learning methods. The program can produce probabilistic forecasts of landslide occurrences in the Ratnapura District since it has been trained to recognize patterns and trends that precede landslides. The Pre-Disaster and Risk Detection AI Prediction System, which has a dedicated landslide prediction module, makes use of AI and predictive analytics to enhance the Ratnapura District's disaster management approach. This component shows the significance of technology innovation in protecting vulnerable communities from natural disasters as part of a complete risk detection framework.**

Keywords: Landslide, Machine Learning, Pre-Disaster.

I. INTRODUCTION

"Pre-disaster" refers to actions, measures, plans, and strategies that are taken in advance of a potential disaster to mitigate its impact, enhance preparedness, and improve the overall resilience of communities and systems. Pre-disaster activities aim to reduce the vulnerabilities of populations, infrastructure, and resources so that they are better equipped to handle and recover from disasters.

Rock, dirt, debris, or a mix of these items moving quickly down a slope or inclination is what geologists refer to as a landslide. Small, localized movements to enormous, disastrous occurrences that encompass sizable areas are all examples of different sizes of landslides. They are frequently brought on by a confluence of natural and man-made events, such as a lot of rain, changes in groundwater levels, clearing of land, building, and slope stability.

Natural disasters like landslides can have a severe effect on communities, leading to fatalities, evictions, and significant infrastructure damage. The risk of landslides is particularly acute in areas like the Ratnapura District that are known for their rough terrain and high rainfall. Effective disaster preparedness and response depend on the early detection and forecast of landslide events in order to reduce the possible consequences. This study introduces a specific component inside the larger Pre-Disaster [1] and Risk Detection AI Prediction System with the goal of forecasting landslides in the Ratnapura District by utilizing the breakthroughs in Artificial Intelligence (AI) [2] and predictive modeling.

A considerable number of landslides occur in the geologically vulnerable Ratnapura District during the monsoon seasons. Accurate forecasting of these phenomena is difficult due to the complexity of the topography and the wide range of weather variables.

By amalgamating diverse data sources, including hydrology data, and geological information the component constructs a comprehensive prediction model. Machine learning algorithms are employed to analyze the complex relationships between these variables and past landslide incidents. Through this analysis, the system learns to identify subtle indicators and triggers that precede landslides, enabling it to provide probabilistic predictions.

This study sets out on a vital goal to deepen our comprehension of landslide dynamics in the difficult Ratnapura District context. We want to develop a sophisticated tool that can foretell probable landslide events by leveraging the combination of AI advancements and predictive modeling. This proactive strategy holds the possibility of reducing the damage that landslides cause to people and infrastructure, leading to more resilient and adaptable communities in landslide-prone areas.

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II. LITERATURE REVIEW

Geological hazards like landslides have the potential to have serious negative effects on the environment, society, and the economy. To reduce their effects and ensure the safety of those living in vulnerable locations, it is essential to predict landslides. The use of geometric data, which consists of numerous topographical and terrain-related parameters, to create precise landslide prediction models has gained popularity in recent years. A summary of significant research works on landslide prediction using geometric data is provided in this review of the literature.

Recursive Feature Elimination for Machine Learning-based Landslide Prediction Models [3]. The recursive feature elimination method, one of the important feature selection techniques in machine learning, is used in this research to propose a landslide prediction model that has not yet been tried in landslide prediction-related applications. Two landslide inventories from landslide-prone locations are used to evaluate the model. The findings demonstrate that the suggested model predicts the likelihood of a landslide with an average accuracy of 91.15% and a sensitivity of 83.4%. The results of this study suggest that, due to its great accuracy, recursive feature reduction can potentially be used to predict landslides.

Landslide susceptibility mapping using XGBoost machine learning method [4]. In summary, this study uses the strength of XGBoost and incorporates many multi-parameter indices to pioneer a comprehensive method to landslide hazard zonation. An accurate representation of the elements affecting the occurrence of landslides is made possible by the complex interaction of topographical characteristics, rainfall information, and vegetation cover dynamics. The XGBoost algorithm enhances this representation by picking important causal components in a hierarchical manner, which then directs the formulation of the LPI. The work increases our understanding of landslide hazard assessment through the use of this novel methodology and provides stakeholders with insightful information for efficient risk management tactics.

Landslide susceptibility mapping using support vector machine for Meghalaya, India [5]. By addressing the dearth of landslide prediction studies in the northeastern region of India, with Meghalaya as a shining example, this study fills a critical research need. In a location susceptible to landslides brought on by excessive rain, they created thorough susceptibility maps by utilizing sophisticated machine- learning tools. These maps serve as a solid platform for informed decision-making and proactive risk management. The study's findings have benefits for both academics and practitioners, strengthening their comprehension of landslide vulnerability while providing practical advice for defending infrastructure and communities against this frequent natural hazard.

Landslide Likelihood Prediction using Machine Learning Algorithms. [6]. The suggested landslide identification model demonstrates an unheard-of level of resilience and efficacy in estimating the likelihood of landslides, and it is supported by the reliable Random Forest algorithm. This impressive performance highlights the model's potential to alter the prediction landscape and improve infrastructure resilience in the face of natural calamities. It is supported by the adaptability of machine learning algorithms. This work pioneers a paradigm change in landslide anticipation through the inventive application of machine learning techniques, lifting the Northeastern United States' readiness and reaction mechanisms to new heights.

Prediction of Earthquake Induced Landslide Using Deep Learning Models [7]. This work is a shining example of development in the field of landslide forecasting. The research community works to increase the precision and effectiveness of landslide prediction models by transitioning from traditional machine learning approaches to cutting-edge deep learning methodology. This investigation makes a crucial contribution to continuing efforts in disaster mitigation and preparedness in the quest to lessen the effect of landslides on human lives and social infrastructure.

Landslide displacement prediction based on integrated neural network. [8] The prediction of GPS base stations on the landslide is the major method used in this paper to determine the degree of landslide surface deformation. The method paired with the prediction model is not thought to reasonably screen the inciting components in the landslide displacement series prediction research. In the meantime, the landslide displacement prediction utilizing the extreme learning machine has very little confidence in the hidden layer's parameter configuration. In order to enhance the quality of model input, the combination model of mean impact value (MIV) and extreme learning machine (MIV- ELM) is first proposed in this study. Second, the Grey-ELM model is created by combining Grey relational degree analysis with the extreme learning machine to estimate how many hidden layer nodes there should be. Thirdly, using the ensemble learning method, an integrated neural network is built using ELM and Grey-ELM. In comparison to the E- ELM model, the integrated neural network's root mean square prediction error is decreased by 25.1% to 10.93 mm, and its goodness of fit increases to 0.998. The integrated neural network possesses a considerable degree of stability and strong generalization ability, according to a comparison of experimental results.

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III. METHODOLOGY

Within the framework of the larger Pre-Disaster and Risk Detection AI Prediction System, this study follows a thorough methodology for the creation and implementation of a landslide prediction component. Geospatial datasets covering slope range, soil type, landform, land use, hydrology, and bedrock geology particular to the Ratnapura District are first gathered from National Building Research Organization (NBRO) and prepared. Using feature engineering approaches, important characteristics from the datasets are extracted and combined to produce a feature matrix that may be used to provide insightful conclusions.

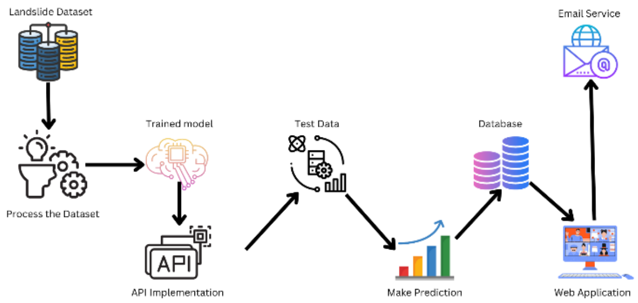

Figure 1: System Diagram

Creating a forecast model for landslide occurrences in the Ratnapura district is the aim of this project. The Random Forest algorithm, a potent ensemble learning technique that mixes numerous decision trees to improve forecast accuracy and robustness, was used to do this.

We collected a comprehensive dataset from National Building Research Organization(NBRO) containing various geospatial and environmental features that are potentially correlated with landslide occurrences. These features may include soil type, land use, land cover, hydrology, bed rock geology and slope range. This raw data was then preprocessed to handle missing values, normalize numerical features, and encode categorical variables appropriately.

An ensemble of decision trees is built by the Random Forest method. Each decision tree is constructed using a random selection of features, and each split is trained using a bootstrapped sample of the original data. This randomization aids in lowering overfitting and improving the model's capacity for generalization.

A user-defined number of decision trees are built throughout the training phase, each using a unique subset of data. The diversity within the trees is ensured by the randomness included during feature selection and data sampling, which together makes for a more accurate and reliable model. Each tree "votes" on the projected class for classification tasks like landslide prediction, and the class with the highest votes becomes the final forecast.

Once the Random Forest model is trained, it can be used to predict landslide occurrences on new, unseen data. For a given set of input features (e.g. soil type, land use, land cover, hydrology, bed rock geology and slope range), each decision tree in the ensemble generates its own prediction. The final prediction is determined by the majority vote among all decision trees.

The number of trees, the maximum depth of each tree, and the amount of features taken into account at each split are only a few of the hyper parameters that govern the behavior of the Random Forest algorithm. We carefully tuned the hyper parameters using methods like grid search or random search to get the configuration that performs the best on the given dataset.

Although the prediction ability of Random Forest models is well established, they can also shed light on the significance of particular features. To determine which environmental elements had the biggest impact on landslide forecasts, we investigated the feature importance produced by the model.

The procedure moves forward with data labeling based on landslide records, classifying cases as having low, medium, or high landslide likelihood by taking into account their geographic coordinates and historical context. For categorization, a reliable Random Forest machine learning method that can handle intricate interactions between the input features is chosen. The labeled dataset is split into training and testing subsets while the model goes through rigorous training and evaluation. Performance indicators like accuracy measure how well the algorithm performs in forecasting landslides.

A large number of decision trees are built during the training phase of the random forests or random decision forests ensemble learning approach, which is used for classification, regression, and other tasks. The class that the majority of the trees chose is the output of the random forest for classification problems. The mean or average prediction of each individual tree is returned for regression tasks. The tendency of decision trees to over fit their training set is corrected by random decision forests. Although they frequently outperform decision trees, gradient boosted trees are more accurate than random forests. However, their effectiveness may be impacted by data peculiarities. [9]

A RESTful API that was created with FAST API and coupled with the produced predictive model offers endpoints that make it easier to communicate with the trained model. Users of the API can enter data such as slope range, soil type, landform, land use, hydrology, and bedrock geology to

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generate forecasts on the likelihood of landslides. The API is accessed through a user-friendly frontend interface that includes input forms for parameter submission and intuitively presents the estimated landslide probabilities through visualizations or numerical values. Using this system user can also send an E-mails to the NBRO when prediction result is Medium risk or High risk.

Following development, the system is put into place and made accessible to users by being deployed into a web server. To ensure reliability and accuracy, stringent testing and validation methods are carried out, matching the model's predictions with actual landslide events. Regular model upgrades using fresh data and continuous system performance monitoring are part of ongoing maintenance. The Ratnapura District's proactive disaster management policies would benefit from the effective and user-friendly Landslide Prediction Component that will be produced using this thorough process.

IV. RESULT AND DISCUSSION

In the context of landslide prediction, the use of the Random Forest algorithm produced outstanding results. The model exhibited its ability to capture complex relationships within the dataset with an amazingly high level of accuracy. Conventional approaches frequently struggle to account for the complexity of elements impacting landslide occurrences, but the Random Forest algorithm's ensemble approach successfully tapped into the collective wisdom of many decision trees. This accomplishment highlights the algorithm's capacity to draw significant patterns from a large number of features, demonstrating its potential to fundamentally alter our knowledge of the mechanics of landslide recurrence.

Although accuracy is a key indicator of a model's success, it takes a subtler approach to translate accuracy into useful insights. It became clear that a fresh approach was necessary to harness the model's predictive capacity for practical decision-making. An original strategy was used to improve the model's predictions as it became clear that accuracy needed to be translated into useful information. Using this Random Forest model achieved nearly 95% accuracy.

A key step was taken: the classification of landslide prediction results into separate risk levels-Low, Medium, and High in order to move from precise forecasts to informed decision-making. This stratification offers a framework for adapting mitigation techniques to the various degrees of risk in addition to giving a more thorough perspective on the prospective landslide events. Stakeholders can more efficiently allocate resources, set priorities for spending, and create intervention strategies by classifying the forecasts. With this tactical change, the predictive model is transformed from a theoretical exercise into a useful instrument that enables decision-makers to take proactive measures to protect vulnerable areas.

The accuracy of the landslide prediction model was significantly improved by the successful application of the Random Forest algorithm. This accomplishment represents a critical turning point in the search for trustworthy forecasting techniques. However, the addition of risk-level classification truly enhances the usability of the model. The model becomes a useful tool in catastrophe management by classifying predictions into Low, Medium, and High risk groups. According to the prediction results, the landslide probability which is having below 35 range will be categorize as a Low risk. And landslide probability which is between 44 and 65 categorize as a Medium risk. Landslide probability which has over 65 value will be categorized as a High risk. The combination of state-of-the-art predictive analytics and useful risk assessment is an excellent illustration of the favorable synergy between technical innovation and practical applicability.

This novel method's usefulness goes beyond statistical prowess because it lays the way for better community resilience and catastrophe preparedness in landslide-prone areas. Local governments and organizations can now direct resources where they are most needed by customizing their response plans based on different risk categories.

In conclusion, the implementation of the Random Forest algorithm not only dramatically improved the landslide prediction model's accuracy but also created the framework for novel approaches to decision-making. The addition of risk-level classification increases the effectiveness of the model, paving the way for better disaster management strategies and enhancing community resilience in landslide- prone areas. This combination of sophisticated predictive analytics and practical risk assessment is evidence of the power of technology innovation to inspire workable solutions, eventually promoting increased readiness and responsiveness in the face of adversity.

V. CONCLUSION AND FUTURE WORK

This paper explored the feasibility of utilizing machine learning, image processing, and computer vision techniques for the identification of disasters and the implementation of an information-sharing platform. The proposed system consists of a prediction component and a user-friendly web application.

Furthermore, expanding the system's reach to predict disasters in larger areas within the Ratnapura district should be a priority. This expansion would require an extensive

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collection of relevant data and the development of predictive models tailored to different regions and disaster types. It would significantly increase the system's availability and usefulness to a broader population.

Additionally, future work should focus on augmenting the information-sharing platform with collaborative features and geospatial visualization tools. Incorporating communication channels for users to report and share information about ongoing disasters, along with geospatial visualization capabilities, would facilitate more effective coordination of response efforts and resource allocation.

In conclusion, this research project has demonstrated the feasibility of using machine learning, and computer vision techniques to identify disasters and create an information-sharing platform. The system's high accuracy and close monitoring capabilities provide valuable tools for disaster management in the Ratnapura district. Future work should encompass the exploration of advanced machine learning algorithms, expanding the system's coverage area, and enhancing the information-sharing platform with collaborative and geospatial visualization features. By pursuing these avenues, the system can contribute significantly to proactive disaster management, improving the safety and resilience of the region.

A crucial next step is the incorporation of collaborative capabilities, which will further enhance the information-sharing platform. Tools for collaborative disaster response allow local residents to actively participate in disaster management in addition to authorized personnel. The platform transforms into a dynamic hub for group catastrophe response by enabling users to share real-time information, coordinate actions, and provide on-the-ground insights. Additionally, the addition of chat capabilities, discussion boards, and collaborative work management tools will promote a feeling of community involvement and instill a sense of shared responsibility for crisis management. By empowering local communities and utilizing the collective wisdom of the group, this inclusive strategy increases the overall safety and resilience of the area.

In conclusion, our vision for the improved information-sharing platform combines superior geospatial visualization capabilities with social functionality. The method makes a substantial advancement towards proactive disaster management by enabling local governments and the general public to actively participate in disaster response activities. By doing this, we not only increase the effectiveness of disaster response, but also fortify community ties, making the Ratnapura district safer and more resilient for all of its inhabitants.

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Volume 7, Issue 11, pp 154-159, November-2023

https://doi.org/10.47001/IRJIET/2023.711022

Citation of this Article:

Sewwandi Kumarasinghe, Vishan Jayasinghearachchi, Pasangi Ratnayaka, "Pre-Disaster and Risk Detection Using AI Prediction System" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 11, pp 154-159, November 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.711022

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