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Combining slope satellite image analysis and artificial intelligence algorithms for highway service level assessment

Combinaison de l'analyse d'images satellites de pente et d'algorithmes d'intelligence artificielle pour l'évaluation du niveau de service des autoroutes

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ABSTRACT: The study proposes an integrated approach using Artificial Intelligence (AI), satellite imagery analysis, and Machine Learning (ML) to address the global challenge of slope instabilities. It emphasizes the importance of comprehensive risk assessment frameworks, particularly focusing on Early Warning Systems (EWS) and decision-making tools. By structuring risk assessment around the hazard-exposure-vulnerability-damage model, the study aims to provide a systematic approach to slope instability management, especially in transportation networks. Additionally, the research evaluates ML algorithms, namely, Multiple linear Regression (MR) and Artificial Neural Networks (ANN), for displacement prediction, highlighting their promising performance while identifying areas for refinement in data preprocessing and model optimization. MR and ANN models consistently achieved high performance, with determinant coefficient (R^2) values of 0.93. This indicates that the model can explain approximately 93% of the variance in the target variable, reflecting strong predictive capability. Despite minor variations in other metrics, such as Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error, the R^2 values remained consistent, emphasizing the robustness of the model in predicting displacements.

RÉSUMÉ: L'étude propose une approche intégrée utilisant l'intelligence artificielle (IA), l'analyse de l'imagerie satellitaire et l'apprentissage automatique (ML) pour relever le défi mondial des instabilités de pente. Elle souligne l'importance de cadres d'évaluation des risques complets, en mettant particulièrement l'accent sur les systèmes d'alerte précoce (SAP) et les outils de prise de décision. En structurant l'évaluation des risques autour du modèle danger-exposition-vulnérabilité-dommages, l'étude vise à fournir une approche systématique de la gestion de l'instabilité des pentes, en particulier dans les réseaux de transport. En outre, la recherche évalue les algorithmes de ML, à savoir la régression linéaire multiple (MR) et les réseaux de neurones artificiels (ANN), pour la prédiction des déplacements, mettant en évidence leurs performances prometteuses tout en identifiant les domaines à affiner dans le prétraitement des données et l'optimisation du modèle. Les modèles MR et ANN ont constamment atteint des performances élevées, avec des valeurs de coefficient déterminant (R^2) de 0,93. Cela indique que les modèles peuvent expliquer environ 93% de la variance de la variable cible, ce qui témoigne d'une forte capacité de prédiction. Malgré des variations mineures dans d'autres mesures, telles que l'erreur absolue moyenne, l'erreur quadratique moyenne et l'erreur quadratique moyenne racine, les valeurs R^2 sont restées cohérentes, soulignant la robustesse des modèles dans la prédiction des déplacements.

Keywords: Slope instability; artificial intelligence.

1 BACKGROUND

Slope instabilities, involving both natural and human-induced processes that alter slope shape, composition, or stability, give rise to a variety of potentially disastrous outcomes, including landslides, debris flow, rock falls, and avalanches (Casagli et al., 2016; Stavrou et al., 2011). These events pose significant threats to individuals, infrastructure, and the environment. Addressing these risks requires ongoing monitoring and the implementation of risk reduction measures. Various methodologies, including remote sensing techniques and Machine Learning (ML), have been explored to comprehend and mitigate slope instabilities (Casagli et al., 2016, 2023; Hammar-Klose & Thieler, 2001; Kuhn & Prüfer, 2014; Mihalić et al., 2015; Nhu et al., 2020; Owusu-Ansah, 2020; Segoni et al., 2018; Stanchev et al., 2013). This work uses ML algorithms to develop predictive models for slope movement detection and stability level classification. The goal is to optimize these models to predict slope movement and classify stability levels accurately. Integrating satellite image analysis and AI algorithms offers promising opportunities for automating processes and enhancing decision-making in slope instability monitoring and risk assessment, addressing the urgent need for effective disaster risk reduction frameworks.

2 METHODOLOGY

The proposed framework integrates AI with satellite imagery to assess highway service levels by utilizing ML to detect slope movements and categorize them into four classes (A-D), with A representing the lowest risk and D indicating the most unstable conditions, through analysis of Interferometric Synthetic Aperture Radar (InSAR) data.

This framework specifically focuses on developing predictive models capable of detecting slope movements using InSAR data, which captures vertical and horizontal displacements on both road infrastructure and surrounding slopes. The data is segregated into two parts: one depicting displacements on the road infrastructure and the other showcasing displacements on slopes adjacent to it. This study particularly concentrates on the vertical displacements observed on the slopes, deliberately excluding other data sources to minimize noise.

The source dataset encompasses 5079 records of displacement values and dates spanning a 7-year period (2016-2023). To streamline the exploration of this dataset, a five-moving window technique is employed to transform it into a new dataset (training dataset) comprising five columns. This curated dataset is more manageable for analysis and serves as the foundation for model training. Table 1 and

Table *2* delineate the step-by-step process involved in processing the source dataset into the training dataset.

This report outlines an experiment for predicting slope movement, where data from the last four slope movements, specifically vertical displacement measurements, were condidered as inputs to forecast the subsequent movement (Next stage).

Table *2* illustrates the sampling strategy for the training data, providing insight into the methodology employed for model training and prediction.

Table 1. Sample of the source dataset (InSAR vertical displacements).

Date	PID1	PID2	PID3	PID4	PID5	PID6
04/10/2016	0	0	0	0	0	0
16/10/2016	2.65	3.08	1.72	1.18	0.55	1.9
28/10/2016	-1.91	-1.32	-1.77	-2.78	-2.5	-1.13
09/11/2016	-1.73	-1.58	-2.88	-3.44	-2.94	-2.02
21/11/2016	-8.23	-8.25	-9.58	-9.71	-8.5	-6.38
03/12/2016	-5.01	-4.22	-5.29	-6.28	-6.9	-5.69

Table 2. Sample of the new dataset (training dataset) produced by a sliding window of five.

FID	stage 1	stage 2	stage 3	stage 4	Next stage (Output)
1	0	2.65	-1.91	-1.73	-8.23
1	2.65	-1.91	-1.73	-8.23	-5.01
2	0	3.08	-1.32	-1.58	-8.25
2	3.08	-1.32	-1.58	-8.25	-4.22
3	0	1.72	-1.77	-2.88	-9.58
3	1.72	-1.77	-2.88	-9.58	-5.29
4	0	1.18	-2.78	-3.44	-9.71
4	1.18	-2.78	-3.44	-9.71	-6.28
5	0	0.55	-2.5	-2.94	-8.5
5	0.55	-2.5	-2.94	-8.5	-6.9
6	0	1.9	-1.13	-2.02	-6.38
6	1.9	-1.13	-2.02	-6.38	-5.69

2.1 Machine learning algorithms

The present study employs a data-driven approach to forecast displacements, utilizing two ML algorithms, namely Artificial Neural Network (ANN) and Multilinear Regression (MR). These algorithms were executed in the R statistical environment (Venables et al., 2024), employing the rminer package (Cortez, 2010). Under both algorithms, cross-validation (5-fold) was implemented for training and validation purposes.

The entire procedure was repeated five times (5 runs) for generalization.

2.2 Model evaluation

The complexity of ML algorithms poses a significant challenge, which can be addressed by evaluating the algorithms based on three primary criteria: accuracy, computational efficiency, and interpretability (Owusu-Ansah et al., 2022). To ensure accuracy, a set of metrics such as Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error

(RMSE), and determination Coefficient (R^2) are considered.

The smaller or closer MAE, MSE, and RMSE are to zero, the higher the accuracy of the predictive model. Similarly, a higher R^2 value indicates greater accuracy of the model. These metrics play a crucial role in assessing the algorithm's efficacy, so their importance must be recognized.

3 RESULTS

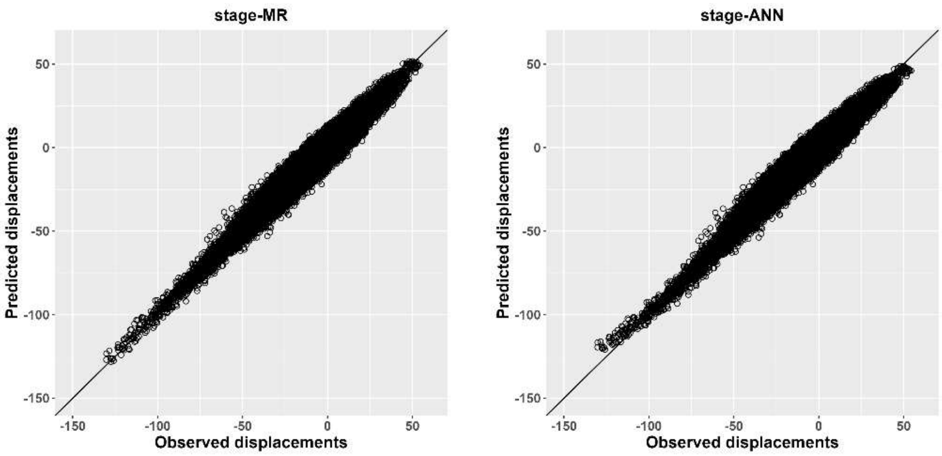
This section summarizes the results obtained from predicting the next stage using ANN and MR algorithms. The focus is on accuracy metrics, with *Table 3* presenting performance metrics for both iterations and algorithms. R^2 indicates a strong correlation, while low values of MAE, MSE, and RMSE emphasize their usefulness in predicting the next stage based on the preceding four stages and time intervals.

This study analyzed the correlation between experimental results and predicted outcomes using two ML algorithms. The correlation analysis, shown in Figure 1, indicated a promising overall performance. Metric values in Table 3 indicate that the results for both ML models perform well and similarly.

Accordingly, additional data pre-processing and the inclusion of other variables are being considered in further experiments aiming to develop more robust models.

Table 3. Models performance evaluations based on MAE, MSE, RMSE, and R^2.

Models	MAE	MSE	RMSE	R^2
MR (stage-MR)	2.19	8.14	2.85	0.93
ANN (stage-ANN)	2.19	8.14	2.85	0.93



a) b)

Figure 1. Scatterplot of the proposed models: a) MR; b) ANN.

4 REMARKS

This study offers valuable insights into the predictive performance of Machine Learning (ML) algorithms for displacements. While the overall analysis shows promising results, there is a need for further refinement in data preprocessing techniques and model optimization to enhance prediction accuracy and reliability.

Correlation analysis, illustrated in Figure 1, reveals consistent and favorable performance trends for both ML algorithms, underscoring their effectiveness. The comparable metric values between the two algorithms suggest consistent performance.

Overall, this study contributes to advancing our understanding of ML-based displacement prediction and suggests avenues for future research, such as exploring additional input variables and refining model optimization techniques, to improve predictive outcomes for practical applications across various domains.

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