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Explainable Machine Learning Model for Ballast Condition Assessment Using Ground Penetrating Radar Scans

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Extended Abstract

Non-destructive tests (NDT) such as GPR (Ground Penetrating Radar), offer an excellent alternative for assessing subsurface conditions. GPR, which employs non-destructive electromagnetic techniques, is both swift and cost-effective in detecting the condition of subsurface features [1-2]. In this study, two methods are explored for assessing ballast condition using GPR. First; ballast condition classification algorithm based on pattern recognition is tried. The classification algorithm uses the K-Nearest Neighbour (KNN) approach, in which, the training phase just stores the dataset and when it gets new data, it classifies that data into a category that is much similar (have more common features among its neighbours) to the new data [3]. Second; in order to address the lack of interpretability of KNN method, the study will develop a framework using an explainable machine learning model [4-5]. This model aims to demonstrate the correlation between GPR scans and various parameters, such as moisture content and the type of fouling material. By using explainable artificial intelligence (XAI) methodologies, specifically Lime and SHAPley Additive explanations, the effect of these fouling parameters on the output responses of GPR scans will be explored. The model will analyse the individual and interactive effects of different variables on both the A-scan and B-scan data obtained from GPR scans. The framework's findings will be validated using GPR scans conducted on lab-built ballast tracks.

The GPR scan will be performed on the artificial ballast track with predetermined fouling level and on the actual track on Korean Gyeongbu high-speed railway line. Simultaneously, we'll perform trail pit excavations on the actual railway line to calibrate and verify our results. For the first approach of ballast condition classification using KNN method, 3 target classes are chosen. Class 1- clean ballast Class 2- Moderately-fouled ballast Class 3- Seriously-fouled ballast. For each target class representative scans (A-Scans) is chosen an average of the first 10 A-scans from lab-built ballast tracks with clean, moderate and seriously fouled condition. The analysis using KNN approach on the lab-built tracks data set graves a promising result that the classification method can be used on the actual site.

For the second approach, to explore the XAI method, six ballast boxes will be constructed: Class 1 (Clean Ballast); a) wet condition b) dry condition. Class 2 (Seriously Fouled Ballast); a) with sand as a fouling material b) with silt as a fouling material. Class 3 (Seriously Fouled Ballast); a) with silt and wet Condition b) with sand and wet condition. The finding of this study seeks to improve comprehension of GPR scans and their correlation with ballast conditions, paving the way for automated and well-informed railway track maintenance and management.

References

[1] Bold, R.D. *Non-Destructive Evaluation of Railway Trackbed Ballast*; The University of Edinburgh: Edinburgh, UK, 2011.

[2] F. N. Birhane, Y.T. Choi and S. J. Lee, "Development of Condition Assessment Index of Ballast Track using Ground-Penetrating Radar (GPR)," *Sensors*, vol. 21, Oct. 2021.

[3] T. Cover and P. Hart, "Nearest neighbor pattern classification, " *IEEE Transactions on Information Theory*, vol. 13 (1), 21–27, 1967.
[4] M. A. Aladsani, H. Burton, S. A. Abdullah and J. W. Wallace, "Explainable Machine Learning Model for Predicting Drift Capacity of Reinforced Concrete Walls," *ACI Structural Journal*, 119(3), 2022.
[5] H. Luo and S. G. Paal, "A locally weighted machine learning model for generalized prediction of drift capacity in seismic vulnerability assessments," *Computer-Aided Civil and Infrastructure Engineering*, vol., 34(11), 935-950, 2019.