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Predicting Isolated Track Defects Using Data-Driven Models for Railway Maintenance Planning

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Abstract

The ability to anticipate future variations in track geometry plays an important role in railway asset management. Reliable prediction of longitudinal level irregularities supports earlier recognition of vulnerable locations, improves the timing of maintenance interventions, and helps reduce operational and maintenance costs. This study investigates machine-learning techniques for forecasting isolated longitudinal-level (LL) defects using EM120 inspection vehicle data. As a case study, almost 17 km of the recently reconstructed Leixões Line in Portugal was considered. For each defect, a local window between ±25 m was extracted to evaluate the behaviour of the fault zone. In this study various prediction machine learning techniques were compared: Artificial Neural Network (ANN), XGBoost, Long Short-Term Memory (LSTM), and Ridge regression and their performance was assessed using R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The results show that LSTM regression model provided the most consistent overall performance across the isolated defects, demonstrating strong predictive capability.

Keywords: track maintenance, machine learning techniques, track geometry prediction, longitudinal level defects, isolated defects, Long Short-Term Memory (LSTM).

1 Introduction

Railway infrastructure is required to provide safe, reliable, comfortable, and cost-effective transport under increasing traffic demand, higher axle loads, and stricter availability requirements [1, 2]. Among the different infrastructure components, track geometry is one of the most important indicators of railway condition because it directly affects vehicle-track interaction, passenger comfort, dynamic forces, component degradation, and maintenance demand [2]. Track geometry is commonly described through parameters such as gauge, alignment, cross-level, twist, and longitudinal level (LL), which are measured periodically by track recording vehicles or diagnostic trains at fixed spatial intervals, often around 0.25 m. These measurements allow infrastructure managers to assess whether the track condition remains within acceptable limits and to plan maintenance operation before defects reach unsafe levels [3, 4].

According to EN 13848 [5], track geometry quality is evaluated by comparing key parameters (longitudinal level, alignment, gauge, cross level, and twist) against established limits. The specific evaluation method depends on whether the irregularities are distributed or isolated. Distributed irregularities are assessed using statistical indicators, such as the standard deviation over 200 m segments to reflect the overall condition of a track section. In contrast, isolated defects are evaluated using local peak amplitudes, such as the peak value of longitudinal level and alignment of the rails in the D1 wavelength range of 3–25 m and the D2 wavelength range of 25–70 m, as well as peak values of gauge, cross level, and twist. Therefore, distributed indicators describe the overall quality of a track section, whereas isolated-defect indicators quantify local extreme deviations that may require targeted maintenance action. This distinction is important because severe local defects can be masked by section-based statistics, even when their peak amplitude is critical for vehicle-track interaction and maintenance planning [6, 7].

Section-based indicators and track quality indices (TQIs) effectively summarize the overall condition of a track segment. For instance, methods compared by Berawi et al. [8], such as the J Synthetic Coefficient, TGI, and the EN 13848-5 approach, rely on combined statistical measures like standard deviations and mean values over fixed track lengths. While useful for assessing general track health, this averaging nature can mask severe, localized peaks. Consequently, an isolated defect might reach a critical amplitude even when the overall section remains within acceptable limits. Therefore, isolated defects require separate analysis from global quality indicators [9]. Moreover, it should be noted that longitudinal level of the rails is particularly important in this context because it describes the vertical geometry of the track along the running direction and is strongly related to ballast settlement, subgrade deformation, support stiffness variation, and maintenance actions [10, 11]. Several studies have shown that longitudinal level is often a key parameter for track geometry degradation and maintenance planning. For example, some researcher focused on longitudinal level because it can deteriorate faster than other geometry parameters and because analysing all geometry parameters simultaneously may be computationally expensive for large datasets [10, 12]. Similarly, Soleimanmeigouni et al. [9] developed a defect-based model specifically for isolated longitudinal level defects and showed that their degradation behaviour can be modelled and used for maintenance decision support. In addition, Nielsen et al. [11] demonstrated that severe local track geometry irregularities are often associated with low track support stiffness and high stiffness gradients, which confirms the relationship between longitudinal-level defects, differential settlement, and local support conditions.

The importance of isolated vertical defects has also been emphasized in recent multidisciplinary research on heaving defects. Tao et al. [13] showed that isolated vertical rail displacement defects may significantly disturb train operation, and that early detection and trend prediction are necessary for predictive maintenance, maintenance prioritisation, and reduction of operational disruption. This supports the need to analyse local defect windows rather than relying only on full-line or section-level statistics.

Track geometry degradation is typically predicted using mechanical, statistical, or by help of machine-learning methods. While traditional models offer physical insights, they rely on simplified assumptions that miss location-specific behaviors [4]. Similarly, statistical and stochastic approaches, such as regression [9], survival analysis [14], and Markov chains [15] are widely used to estimate defect evolution and maintenance probabilities. However, a single statistical formulation is often insufficient to capture complex, real-world variables like local support conditions, maintenance history, measurement noise, and irregular inspection intervals [6, 10].

Machine-learning techniques have therefore become increasingly attractive for track geometry prediction because they can learn nonlinear and location-dependent relationships from historical measurements [16]. Han et al. [12] compared support vector machines, grey models, and deep neural networks for longitudinal-level prediction and showed that model performance differs according to wavelength range, rail side, and track condition. This indicates that no single techniques can be assumed to perform best for all track conditions, and that comparative assessment is necessary to identify the most suitable prediction method for a specific railway line and defect type.

Despite the progress in track geometry degradation modelling, most existing approaches are mainly developed for section-based quality indicators or distributed irregularities, while less attention has been given to the localized evolution of isolated longitudinal-level defects. This study addresses this gap by focusing on individual defect zones rather than global track sections. The proposed approach combines the EN 13848 [5] concept of isolated local exceedances with a localized prediction framework, in which short windows around each defect are analysed independently. By evaluating Ridge regression, ANN, XGBoost, and LSTM, this study examines whether machine-learning techniques based on regularized linear learning, nonlinear neural-network learning, gradient-boosted decision trees, and recurrent sequence learning can predict the future evolution of isolated LL defects under real inspection conditions. Such prediction is important for condition-based maintenance, since anticipating defect evolution can support more efficient intervention planning and contribute to optimal maintenance scheduling before local irregularities reach critical limits [5, 17].

2 Case study description

The Leixões Line is one of the historical railway links within the Porto Metropolitan Area. It was inaugurated in 1938 with the main purpose of connecting the Port of Leixões to the Portuguese national railway network, and its operation was originally dominated by freight transport. The line extends for 20.9 km and passes through highly urbanized areas, including important municipalities such as Porto, Matosinhos, and Gondomar. Regular passenger operation was suspended in 1966, temporarily resumed between 2009 and 2011, and has recently been restored following modernization works promoted by Infraestruturas de Portugal, Comboios de Portugal, and the Municipality of Matosinhos. At present, the line operates under mixed traffic conditions, including 60 passenger services on weekdays and a reduced but regular timetable during weekends and public holidays. The selected corridor contains 35 curves, corresponding to approximately 11.5 km of curved alignment, with the smallest circular curve radius being about 274 m. For the present analysis, almost 17 km common section was adopted, since this was the part of the track consistently available in all inspection campaigns.

2.1 EM120 data source and synchronization

The original measurements were collected by the EM120 vehicle inspection over approximately 17 km of the Leixões railway line in Portugal during six years: 2020, 2021, 2022, 2023, 2024, and 2025.

Before model development, the EM120 measurements from the six inspection campaigns were preprocessed and synchronized. This step was necessary because repeated track geometry inspections do not always record the same physical point at exactly the same chainage, due to small positioning errors, odometer deviations, or differences in the measurement starting point. If these offsets are not corrected, the same defect may appear at slightly different positions in different years, which can lead to incorrect comparison of defect evolution and reduce the reliability of the prediction models. Therefore, the position column was checked, the longitudinal-level data required for the study were retained, and all inspection profiles were shifted onto a common chainage reference. After synchronization, each row of the dataset represents the same physical track location for all inspection years, allowing the temporal evolution of each localized defect to be analysed consistently.

Figure 1 illustrates the effect of the synchronization process for the longitudinal level defect of the left rail at position 3489 m (LL_3489_L). Before synchronization, the six inspection profiles are horizontally shifted, and the main peaks and valleys do not occur at the same positions. After synchronization, the profiles become better aligned, and the same local irregularity can be compared consistently between 2020 and 2025. This confirms that synchronization is an essential preprocessing step before extracting the ±25 m defect window and training the prediction models. For longitudinal level, two wavelength ranges are commonly considered: D1, corresponding to short-wave irregularities between 3 m and 25 m, and D2, corresponding to longer-wave irregularities between 25 m and 70 m. In this study, only the D1 range was considered because the objective was to analyse localized short-wave longitudinal-level defects, which are more directly related to local vehicle-track dynamic effects and safety-relevant local exceedances. Therefore, a ±25 m window was adopted around each detected defect to include the peak amplitude and the surrounding transition zone, while limiting the influence of unrelated track behaviour outside the local defect area. This also provided a consistent input length for all prediction models [5, 6].

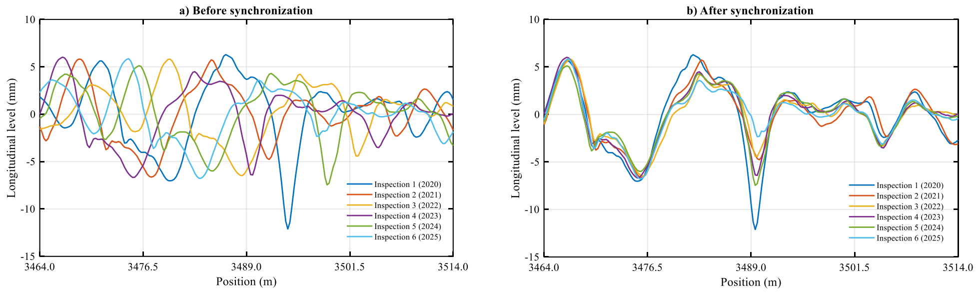

Figure 1: Longitudinal level profiles (a) before synchronization, (b) after synchronization, where the main peaks and valleys are better aligned.

2.2 Selection of longitudinal level and isolated defects

In this study, isolated longitudinal-level defects were selected using a local peak-amplitude approach consistent with the EN 13848-5 [5] concept of isolated defects. Both upward and downward longitudinal-level defects were considered by using the absolute value of the local peak amplitude. Since the objective was to analyse short-wave localized longitudinal-level defects, only the D1 wavelength range was considered. Based on the applicable speed range of the analysed Leixões Line section, the selected 12 mm screening threshold corresponds to the upper range of the D1 alert limit for longitudinal-level isolated defects. Therefore, the defects represent relevant early-warning longitudinal-level irregularities for localized prediction, but they do not correspond to immediate action limit exceedances. This distinction is important because the purpose of this study is not to identify emergency safety exceedances, but to predict the evolution of localized longitudinal-level defects before they reach more critical maintenance or safety levels.

Table 1 presents the longitudinal level limits across various speeds and wavelengths as extracted from the EN standard and based on these parameters, the isolated track faults are defined in Table 2.

Speed range	AL D1 (mm)	AL D2 (mm)	IL D1 (mm)	IL D2 (mm)	IAL D1 (mm)	IAL D2 (mm)
V ≤ 80 km/h	12-18	N/A	17-21	N/A	28	N/A
80 < V ≤ 120 km/h	10-16	N/A	13-19	N/A	26	N/A
120 < V ≤ 160 km/h	8-15	N/A	10-17	N/A	23	N/A
160 < V ≤ 230 km/h	7-12	12-16	9-14	14-20	20	24
230 < V ≤ 300 km/h	6-10	8-12	8-12	10-14	16	18
300 < V ≤ 360 km/h	6-8	8-10	7-10	8-12	14	16

Table 1: Limit values for longitudinal-level isolated defects related to various speeds (EN 13848-5 [5]), featuring AL (Alert Limit), IL (Intervention Limit), and IAL (Immediate Action Limit) for wavelengths D1 (3–25 m) and D2 (25–70 m).

Defect ID	Rail	position (m)
LL_3489_L	Left	3489
LL_3870_R	Right	3870
LL_6588_R	Right	6588
LL_6961_L	Left	6961
LL_8055_L	Left	8055
LL_11362_L	Left	11362

Table 2: Longitudinal-level isolated faults for localized prediction.

2.3 Localized fault prediction formulation

The prediction task was formulated separately for each isolated longitudinal-level defect. Rather than predicting the condition of the full track section, each defect was analysed independently within its extracted ±25 m window. In this window, each measured track position represents one data sample, and the objective is to predict the longitudinal-level value at the same position in the next inspection campaign. Accordingly, the final target is the measured 2025 longitudinal-level profile within each localized defect window.

For each measured track position, the input features were derived from previous inspection (2020-2024) and included the track position, the relative distance from the defect, the longitudinal-level values from consecutive inspections, the amplitude change, the deterioration rate, and the time interval to the next inspection. It should be noted that, the deterioration rate was computed as the amplitude change divided by the time interval between inspections, accounting for the unequal spacing of EM120 campaigns.

Earlier inspections were used for training, while the final inspection was reserved to evaluate the prediction of the 2025 profile. The machine learning techniques were applied separately to each defect to avoid mixing different local degradation mechanisms and to identify the most suitable technique for each isolated defect.

3 Application of Machine Learning Techniques for Detecting Railway Track Defects

Four machine-learning techniques with different learning mechanisms were evaluated within a localized defect-based prediction framework to identify the most suitable approach for forecasting the future longitudinal-level profile of isolated track faults. Specifically, Ridge regression, ANN, XGBoost, and LSTM were selected because they rely on distinct learning principles, allowing the framework to be assessed under different predictive behaviours. Ridge regression is a regularized linear method that minimizes the prediction error while adding an L2 penalty term. This L2 term is the sum of the squared values of the regression coefficients. In practice, it discourages the model from assigning very large weights to the input variables, making the prediction more stable and reducing overfitting. Therefore, Ridge regression is useful when the input variables are correlated or when a simpler and more robust benchmark model is needed [18]. ANN models use interconnected neurons and nonlinear activation functions to approximate complex relationships between inputs and outputs, but their performance depends on the network structure, number of neurons, activation functions, and training data [19]. XGBoost is an ensemble tree-based method that sequentially combines weak learners by minimizing a regularized loss function, making it effective for nonlinear relationships and small-to-medium datasets, although it may require careful hyperparameter tuning [20]. LSTM networks are a recurrent neural-network architecture with memory gates, which makes them suitable for learning temporal dependencies between inspection campaigns, but they are more computationally demanding and sensitive to the amount of available sequential data [21]. Then, the comparative analysis was carried out under the performance indices including R2, RMSE, and MAE. A short description of each model and its approach is provided in Table 3.

Technique	Approach	Characteristics of the model
Ridge regression	Regularized linear model	Baseline model for approximately linear degradation; useful when data are limited and overfitting must be controlled [18].
ANN	Feed-forward neural network	Nonlinear model able to learn complex relationships between local geometry features and future amplitudes [22].
XGBoost	Gradient-boosted decision trees	Tree-based ensemble model effective for nonlinear tabular data and interactions between features [20].
LSTM	Recurrent neural network	Deep-learning sequence model designed to learn temporal dependencies between inspections [21].

Table 3: Prediction models selected for comparison and their methodological roles.

The main aim of this study is to comparatively analyse the performance of various machine-learning techniques for predicting localized longitudinal-level isolated defects on the Leixões railway line. The complete workflow used in this study is shown in Figure 2 The workflow starts from the raw EM120 measurements and ends with model comparison for the localized isolated faults.

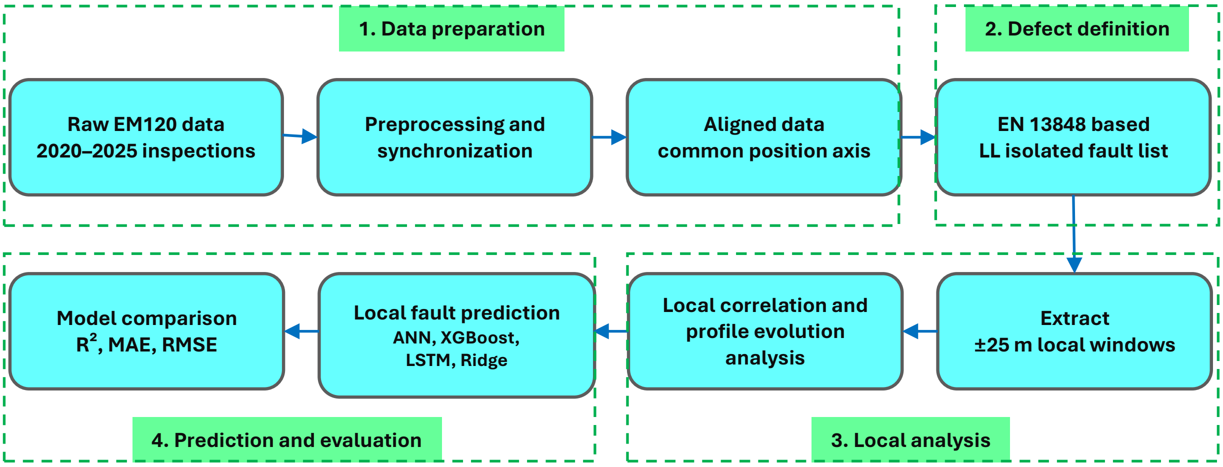

Figure 2: Methodological workflow for localized longitudinal-level isolated fault prediction.

4 Results and Discussion

The prediction results were evaluated independently for each isolated longitudinal-level defect using the measured 2025 profile as the external test target. The performance indicators are the coefficient of determination (R^2), the mean absolute error (MAE), and the root mean square error (RMSE). Higher R^2 values indicate better agreement with the measured profile shape, whereas lower MAE and RMSE values indicate smaller pointwise prediction errors.

Overall, the models performed well for most defect locations, but their relative performance varied with the local defect behaviour. This confirms that localized longitudinal-level defects do not necessarily evolve according to a single uniform degradation pattern. The following subsections present the results for each fault.

4.1 Visual assessment of localized defect prediction results

Figure 3 visualizes the measured and predicted 2025 longitudinal-level profiles for the six isolated defects, providing a clear understanding of the performance of the different prediction models. In most cases, the models follow the measured profile with good agreement, particularly for LL_3870_R, LL_8055_L, and LL_11362_L. The largest differences are observed for LL_6961_L, indicating that this defect has a more irregular behaviour and is more difficult to predict. The result of LL_6961_L suggests that the defect may have undergone a non-stationary change between inspections, possibly due to local maintenance, measurement synchronization sensitivity, abrupt support-condition variation, or a change in defect shape rather than a simple amplitude evolution. For this reason, LL_6961_L should be interpreted as a challenging local case rather than as representative of the general model behaviour.

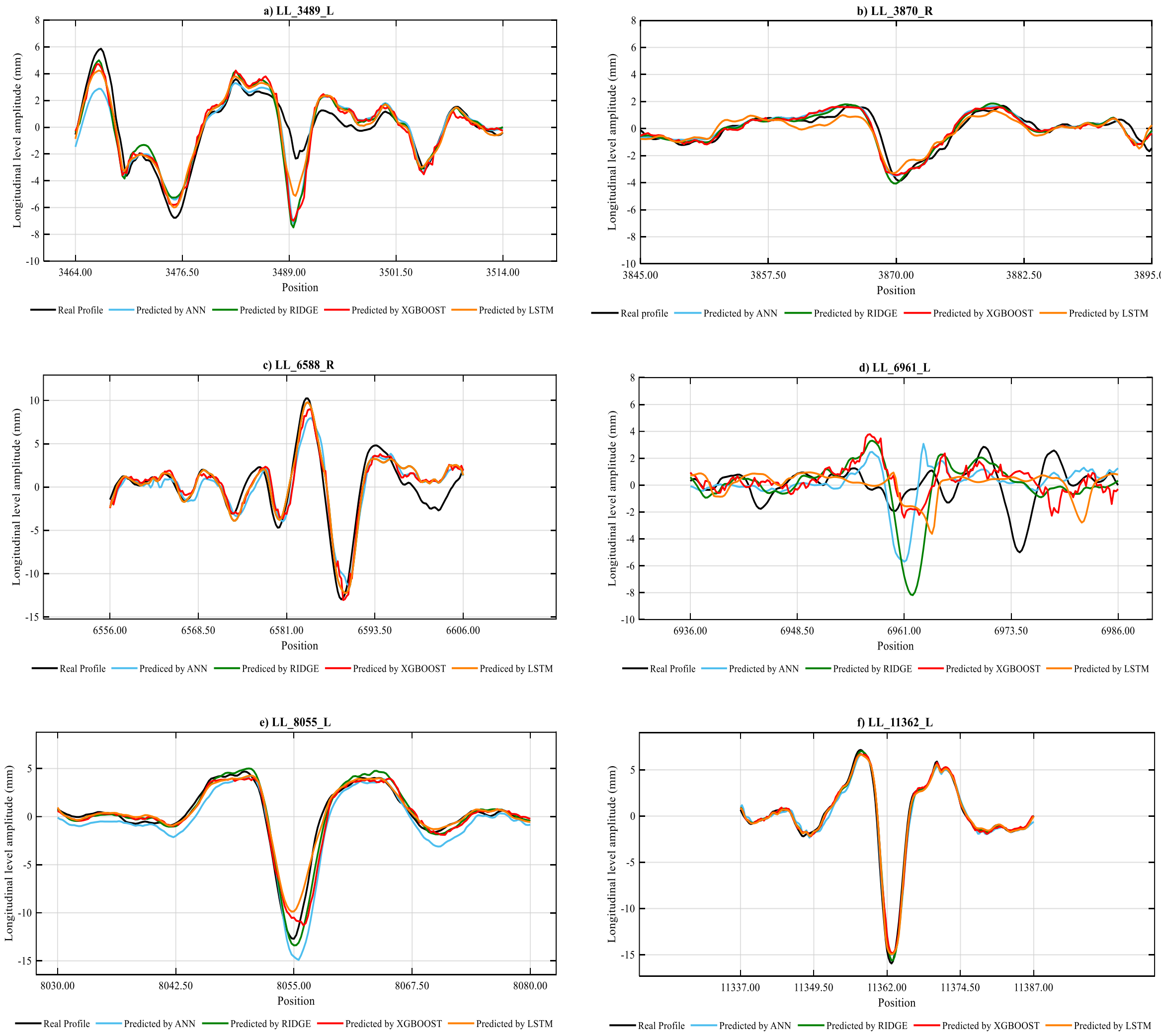

Figure 3: Comparison of measured and predicted 2025 longitudinal-level profiles for the six localized isolated defects.

4.2 Discussion of model performance

Table 4 summarizes the prediction results obtained for each isolated defect and compares the performance of the different machine-learning techniques using R^2, MAE, and RMSE. The results show that the performance of the techniques depends strongly on the local characteristics of each isolated longitudinal-level defect. For LL_3489_L, all techniques produced positive R^2 values, with LSTM achieving the best performance, indicating that the 2025 profile was captured with reasonable accuracy. For LL_3870_R, the differences between ANN, XGBoost, and Ridge were small, while ANN provided the highest R^2 and the lowest RMSE, suggesting a stable and predictable local evolution. For LL_6588_R, LSTM achieved the best performance in all three indicators, with $R^2 = 0.8783$, MAE = 1.0417 mm, and RMSE = 1.3964 mm, while XGBoost and Ridge also showed close results. The most challenging case was LL_6961_L, where ANN, XGBoost, and Ridge produced negative R^2 values. This means that their prediction errors were larger than the error obtained by simply using the mean value of the measured 2025 profile as a reference. This behaviour is mainly related to the irregular evolution of this defect, where the predicted profiles show large local deviations and do not correctly match the amplitude and position of the measured peaks and troughs. Although LSTM was the only technique with a positive R^2 for this defect, ANN produced slightly lower MAE and RMSE, indicating that the interpretation of this case depends on the selected evaluation criterion. For LL_8055_L, LSTM provided the best overall performance, while Ridge was also highly competitive, showing that part of the local evolution was nearly linear. Finally, for LL_11362_L, all techniques achieved very high R^2 values; LSTM provided the best profile-shape agreement, whereas Ridge produced the lowest MAE and RMSE.

Overall, LSTM demonstrated the most consistent performance across the defects, although Ridge and ANN were more effective for specific cases depending on the selected evaluation criterion.

Defect	**Technique**	**R^2**	**MAE (mm)**	**RMSE (mm)**
LL_3489_L	ANN	0.7296	0.8256	1.3014
	XGBoost	0.7476	0.8379	1.2576
	LSTM	**0.8644**	**0.6491**	**0.9217**
	Ridge	0.7336	0.8414	1.2916
LL_3870_R	**ANN**	**0.8980**	0.2840	**0.3971**
	XGBoost	0.8874	0.2979	0.4173
	LSTM	0.8156	0.4199	0.5340
	Ridge	0.8892	**0.2788**	0.4139
LL_6588_R	ANN	0.8205	1.4174	1.6959
	XGBoost	0.8649	1.1467	1.4714
	LSTM	**0.8783**	**1.0417**	**1.3964**
	Ridge	0.8578	1.1925	1.5096
LL_6961_L	ANN	-0.4549	**1.1674**	**1.6552**
	XGBoost	-0.9174	1.3460	1.9001
	LSTM	**0.5612**	1.2209	1.7146
	Ridge	-1.8051	1.5257	2.2983
LL_8055_L	ANN	0.8314	0.9756	1.4406
	XGBoost	0.9221	0.5866	0.9788
	LSTM	**0.9572**	**0.4532**	**0.7257**
	Ridge	0.9527	0.5286	0.7628

Defect	Technique	R^2	MAE (mm)	RMSE (mm)
LL_11362_L	ANN	0.9813	0.4435	0.6137
	XGBoost	0.9881	0.2930	0.4883
	LSTM	**0.9916**	0.4532	0.7257
	Ridge	0.9887	**0.2823**	**0.4764**

Table 4: Prediction performance of the tested machine learning techniques for longitudinal-level defects.

5 Conclusions and Contributions

This study developed and evaluated a localized prediction framework for isolated longitudinal-level defects using EM120 track geometry measurements collected on the Leixões railway line between 2020 and 2025. Instead of predicting the complete line condition, the analysis focused on six isolated longitudinal-level defects and extracted a local window around each fault. This formulation is more suitable for local maintenance planning because it preserves the shape and amplitude of short defects that may be hidden by section-based quality indicators.

From a maintenance and asset-management perspective, LSTM can be considered the best preliminary model for this dataset because it most often achieved the highest R^2 and the lowest error values, particularly at LL_3489_L, LL_6588_R, and LL_8055_L. However, Ridge remains valuable as a transparent benchmark because it gave the lowest pointwise errors at LL_11362_L and the lowest MAE at LL_3870_R. XGBoost was also consistently competitive, especially for locations where the defect evolution involved nonlinear relationships among the selected input features. Therefore, the final model choice should consider both prediction accuracy and interpretability: LSTM is recommended as the strongest overall model, while Ridge and XGBoost should be retained as reliable benchmark models for comparison.

The study also has limitations. The available dataset contains only six inspection campaigns, and the final assessment was performed using the 2025 inspection as the external test case. Future work should include additional inspection years, maintenance records, train loading information, and environmental variables. These additional data would help distinguish true degradation from measurement variability and would allow the prediction models to be updated as more inspections become available.

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