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A Stress-Informed Approach with Vibration Analysis for Railway Safety Monitoring

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Abstract: In this study, two novel approaches, a Stress Informed Approach and Vibration Analysis in machine learning and Intelligent Railway Safety Monitoring, are presented. These methods enhance real-time detection and prediction of structural risks, supporting safer and more efficient railway operations. The stress-informed component relies on geometric deformation analysis, calculating internal stresses using curvature and material stiffness to identify mechanical strain. Simultaneously, vibration analysis evaluates natural frequency shifts to detect structural anomalies indicative of stiffness degradation. High-resolution point cloud data were used to extract spatial features such as slope and curvature, which served as inputs to a machine learning classifier. A random forest model was trained to categorize risk into three classes, achieving 96.8% accuracy and a 95.1% F1-score. These results confirm the reliability of integrating physics-based diagnostics with intelligent modeling. The proposed framework offers a scalable solution for predictive maintenance, enabling early intervention and improved safety in modern railway infrastructure.

Keywords: Point Cloud Feature Extraction, Point Cloud Feature Extraction, Structural Safety Monitoring, Vibration-Based Fault Detection

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Research paper

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1 INTRODUCTION

Monitoring in the context of engineering systems refers to the continuous or periodic observation, measurement, and assessment of infrastructure conditions to ensure operational safety, detect potential failures, and support decision-making processes. This practice is crucial in environments where early detection of anomalies can prevent catastrophic incidents and reduce maintenance costs [2]. In railway systems, monitoring involves evaluating various parameters such as structural integrity, track alignment, vibration, and environmental factors using a combination of sensors and data processing methods [15]. The integration of modern sensing technologies, such as LiDAR and computer vision, has significantly enhanced the ability to capture high-resolution spatial data for accurate and real-time infrastructure assessment [14].

Intelligent railway safety systems represent a shift from traditional rule-based safety protocols toward adaptive, data-driven solutions that utilize artificial intelligence (AI) and sensor fusion to anticipate and mitigate risks. These systems leverage high-frequency monitoring data, such as LiDAR point clouds, vibration signals, and environmental parameters, to detect anomalies before they evolve into critical failures. Recent studies have demonstrated the potential of intelligent methods, including deep learning, semi-supervised models, and sensor fusion, in improving obstacle detection, anomaly classification, and infrastructure condition monitoring with high precision and robustness in real-time applications [1-2], [5]. The goal of such systems is not merely to respond to failures but to proactively ensure safety by predicting and preventing hazards under diverse operating conditions.

Stress-informed monitoring involves evaluating internal stresses in rail structures induced by external loads, often using curvature-derived metrics to assess mechanical integrity in fatigue-prone zones [13]. Complementarily, vibration analysis identifies structural anomalies through deviations in natural frequencies and modal responses, indicative of stiffness loss or material degradation [11-12]. These techniques leverage foundational mechanical models such as the Euler–Bernoulli beam theory, represented as

$$q(x,t) = \frac{\partial^2}{\partial x^2}\left(EI\,\frac{\partial^2 w(x,t)}{\partial x^2}\right) + \rho A\,\frac{\partial^2 w(x,t)}{\partial t^2}, \quad (1)$$

Where w (x, t) denotes displacement, E Young's modulus, I moment of inertia, ρ material density, and q (x, t) external loading. This formulation enables accurate modelling of dynamic rail deflections. Additionally, damage localization is enhanced using the modal curvature index, defined as:

$$\Delta\phi_i(x) = \left|\phi_i^{'}(x)_{\text{damaged}} - \phi_i^{''}(x)_{\text{healthy}}\right|, \quad (2)$$

This captures changes in the second derivative of mode shapes between damaged and undamaged states [13]. Enshaeian et al. [7] validated axial stress estimation from field-measured vibration data, while Li et al. [6] employed curvature-difference analysis for hidden defect detection. Such physics-informed diagnostics, when integrated with machine learning, offer a robust framework for intelligent railway safety monitoring [15].

Numerous studies have leveraged machine learning and sensor data fusion to enhance obstacle detection and structural risk assessment in rail systems. For instance, Nan et al. [4] utilized 3D LiDAR for precise obstacle detection, while Ge et al. [5] proposed a semi-supervised learning model that effectively detects unknown anomalies using vision-LiDAR fusion. Additionally, Qu et al. [9] improved obstacle detection through adaptive Euclidean clustering, and Tang et al. [3] applied camera-LiDAR integration for real-time track geometry mapping. These contributions underscore the growing reliance on sensor-driven AI techniques. However, many prior models predominantly focus on visual, spatial, or environmental parameters, often neglecting the mechanical behavior of rails under stress and dynamic loads.

In contrast, the present study introduces a stress-informed and vibration-based monitoring framework that integrates geometric derivatives (slope, curvature), physical stress estimation, and vibrational frequency analysis with Random Forest classification. By combining spatial, mechanical, and dynamic features, the proposed model provides a more comprehensive approach to intelligent railway safety monitoring, surpassing prior limitations and enabling more effective risk differentiation under real-world conditions.

2 LITERATURE REVIEW AND PREVIOUS WORKS

One of the most significant advances in railway safety monitoring has been the fusion of LiDAR data with machine learning techniques to detect obstacles, monitor infrastructure, and assess operational risks. Nan et al. [4] achieved a stable detection rate (STDR) of over 95% using a 3D LiDAR-based obstacle detection algorithm, effectively addressing geometric distortion and terrain variation. Similarly, Wen et al. [1] improved obstacle detection in adverse weather conditions by introducing a dual-modality fusion strategy, which reported an mIoU of 87.38%, demonstrating robustness under challenging conditions.

Chen [14] enhanced tunnel risk control through CNN models optimized with Bayesian learning, providing high accuracy and interpretability. Cuomo et al. [11] introduced a hybrid PINN-EKF model for vertical displacement prediction in rail structures, thereby improving precision in dynamic environments. Ge et al. [5] extended anomaly detection using semi-supervised learning with a fusion of vision and LiDAR data, reaching mAP and mAR values of 92.2% and 94.5%, respectively. These studies illustrate the potential of integrated ML-LiDAR systems for reliable railway safety applications.

Building on these foundations, researchers have developed innovative algorithms to enhance obstacle detection accuracy. Wang et al. [12] integrated incremental clustering with lightweight convolution, achieving a 90.3% recall rate and improving system responsiveness. Qu et al. [9] resolved segmentation inconsistencies by introducing adaptive distance thresholds in Euclidean clustering, enhancing accuracy in sparse data regions. Cserép et al. [13] addressed infrastructure segmentation challenges by applying efficient fragmentation methods on dense LiDAR datasets, promoting automation and scalability. Chen et al. [10] combined YOLO-V5 with LiDAR point cloud fusion to reduce false positives, and Cserep [15] offered an annotated dataset of Hungarian railway infrastructure, supporting model training and benchmarking. Together, these works provide a solid foundation for intelligent obstacle detection and monitoring; however, many rely solely on visual or geometric data, overlooking deeper physical interactions, such as stress and vibration.

To address these gaps, recent studies have emphasized the inclusion of stress analysis and vibration diagnostics in railway monitoring systems. Enshaeian et al. [7] proposed a vibration-based system for axial stress estimation using FEM simulations, verified through field testing. Li et al. [13] applied modal curvature analysis to detect internal rail defects, maintaining error rates below 5% for cracks as small as 6 mm. Belding et al. [16] and Enshaeian et al. [17] further demonstrated the value of ML in linking vibration modes to stress and neutral temperature using data-driven models validated by finite element analysis. Tang et al. [3] developed a real-time camera–LiDAR fusion system for accurate track geometry estimation, while Masiero et al. [2] applied clustering for structural health monitoring in bridges. Auersch [19] introduced fast physics-based models for vibration prediction, and Raut et al. [20] integrated AIoT platforms for condition monitoring and real-time decision-making. These studies collectively highlight the growing relevance of hybrid methods that blend mechanical insight with AI for predictive safety evaluation.

Operational implementation of these techniques has also been validated through in-situ monitoring systems and practical data handling strategies. Jensen et al. [21] developed a real-time system using sound and vibration sensors on passenger trains, achieving over 84% classification accuracy for track anomalies. Delia Sandhy et al. [22] demonstrated that smartphone-linked accelerometers combined with K-means clustering could detect damage patterns across multiple rail conditions.

Lin and Zhuang [23] proposed a hybrid preprocessing framework that uses statistical filters and unsupervised ML to qualify large rail vibration datasets, increasing the reliability of subsequent analytics. For bridge health monitoring, Dutta and Nath [24] applied LSTM neural networks to predict strain responses from sparse sensor data, reducing hardware costs. Kaewunruen et al. [25] showed that vibration-based train weight estimation could support mobile inspection systems. Moreover, Kashyzadeh and Ghorbani [26] used ANN models to correlate machining conditions with fatigue life in rail alloys, while Reza Kashyzadeh et al. [27] predicted concrete compressive strength under varying curing environments using genetic algorithm-optimized neural networks. These diverse applications underscore the versatility of AI and vibration data in improving infrastructure diagnostics and lifecycle management.

3 MATERIALS AND METHODS

3.1. Data Source and Preprocessing

This study employs high-precision LIDAR-based point cloud datasets of rail and cable infrastructure to predict railway safety risks. The dataset, sourced from Cserep, Mate (2022), provides detailed annotations of the railway environment. The point cloud data includes spatial coordinates (X, Y, Z) and intensity values, which are fundamental to understanding geometric deformations and material anomalies along railway tracks [8], [3].

4.2. Proposed Method

To detect structural defects and environmental anomalies, the following critical features were engineered:

Slope (S) and curvature (κ) of the rail geometry were computed using discrete derivatives from 3D spatial coordinates:

$$S = \left(\frac{dX}{dx}\right)^2 + \left(\frac{dY}{dx}\right)^2 + \left(\frac{dZ}{dx}\right)^2 \tag{3}$$

$$\kappa = \frac{|\, r'(s) \times r''(s) \,|}{|\, r'(s) \,|^3} \tag{4}$$

Where, r(s) is the position vector along the rail, derived from the point cloud.

Stress Estimation: Surface stress concentration was estimated based on local geometric deformations using the curvature κ and material stiffness E, adopting the bending stress formula:

$$\sigma = E.\kappa.y \tag{5}$$

Where y is the distance from the neutral axis [7], [6].

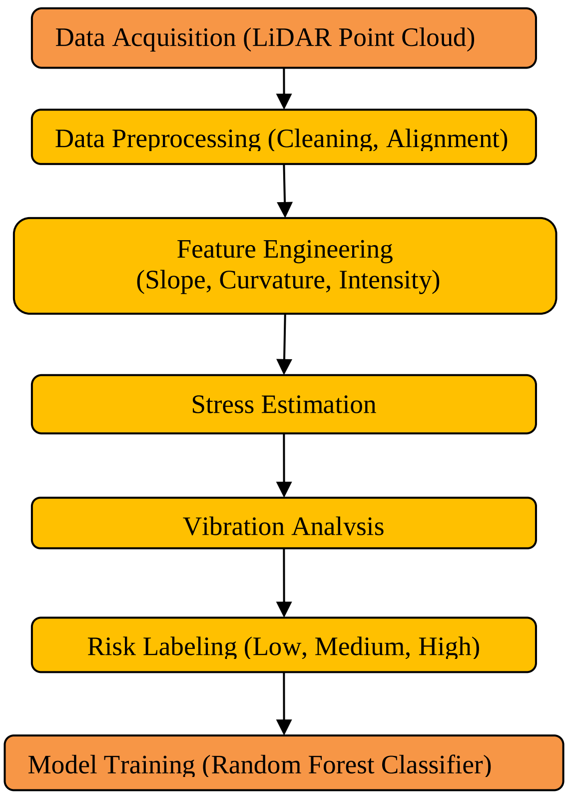

Fig. 1 Workflow of Proposed Method.

Vibration Analysis: Local vibrational sensitivity was inferred using the natural frequency of beam segments modeled by:

$$f_n = \frac{1}{2\pi}\sqrt{\frac{k}{m}} = \frac{1}{2\pi}\sqrt{\frac{EI}{\rho A L^4}} \tag{6}$$

Where E is Young's modulus, I is the moment of inertia, ρ is the material density, A is the cross-sectional area, and L is the span length. This approach aligns with current methodologies applied in vibration-based rail stress analysis [7], [2].

Risk Labeling: Based on deviations in slope, curvature, and intensity, a synthetic labeling scheme was created. Each data point was categorized into "Low," "Medium," or "High" risk classes.

4.3. Machine Learning Model Development

A Random Forest classifier was employed for its robustness in handling heterogeneous, high-dimensional input. The dataset was split into 80% training and 20% testing subsets. Feature importance analysis guided model refinement. Hyperparameters (e.g., number of estimators, maximum depth) were tuned using grid search with 5-fold cross-validation. The classifier was trained to predict risk labels based on spatial, stress, and vibrational indicators, enabling intelligent monitoring of railway safety risks [3], [2]. Figure 1 shows the workflow of the proposed method for intelligent railway safety monitoring.

4 RESULTS AND DISCUSSION

Structural and dynamic evaluations were conducted to assess the mechanical integrity of rail segments under operational and environmental stresses. These evaluations formed the basis for feature derivation and risk classification in the subsequent modelling phase.
Figure 2 illustrates the spatial distribution of Z and Intensity values, revealing distinct groupings that correspond to varying risk levels.

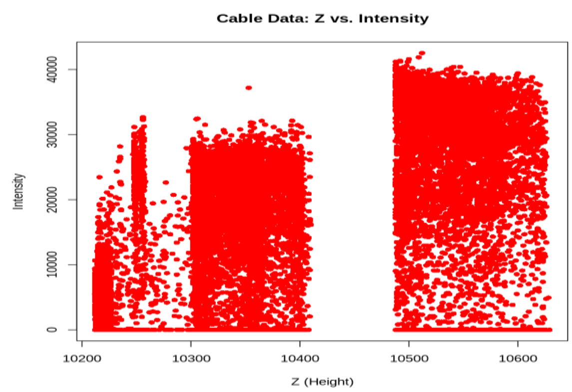

Fig. 2 Structural Feature Variation Across Cable Dataset.

The visible separations and variability within the data underscore its suitability for developing effective machine learning-based classification models. "Table 1" presents calculated axial stress levels across three rail sections, derived from curvature measurements and geometric offsets using the Euler-Bernoulli stress formulation. Elevated stress values, such as in section S3 (89.6 MPa), indicate increased mechanical load concentrations and potential fatigue zones [6], [18].

Table 1 Estimated Axial Stress Along Rail Sections

Section	Curvature	Distance from	Estimated

ID	(κ)	Neutral Axis (y) [mm]	Stress (σ) [MPa]
S1	0.0021	30	63.0
S2	0.0016	25	40.0
S3	0.0032	28	89.6

Note: Stress was calculated using the formula $\sigma = E \cdot \kappa \cdot y$ with $E = 1.0 \times 10^5$ MPa. Higher stress indicates increased structural risk. Reference: [6], [18].

Figure 3 shows a stress–curvature density contour plot, revealing a non-linear correlation between curvature (κ) and estimated stress (σ), with stress intensity increasing around $\kappa \approx 0.002$, indicating areas of structural risk concentration. The distribution suggests heterogeneity in material behavior across the monitored rail segment.

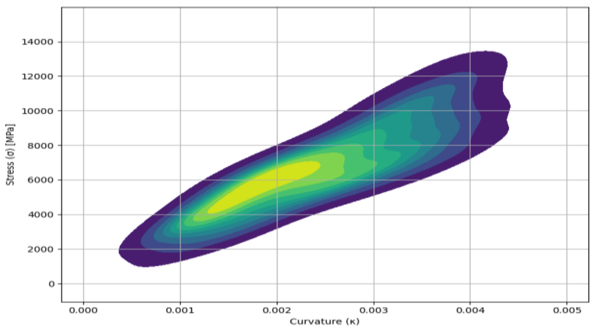

Fig. 3 Relationship Between Induced Stress and Geometric Curvature.

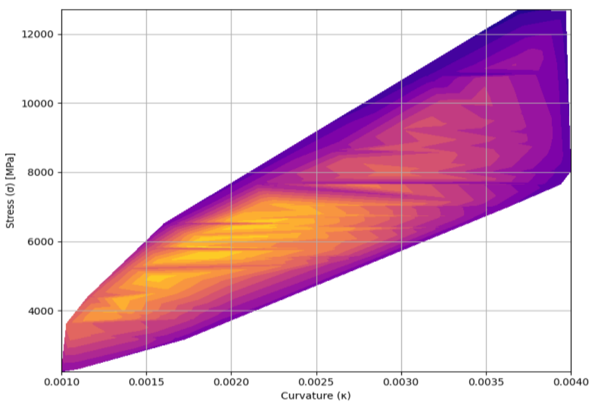

Fig. 4 Probability Landscape of Stress Distribution Relative to Curvature.

"Table 2" summarizes modal frequency measurements for the first two vibration modes, revealing notable deviations from the baseline. Significant reductions in modal frequencies, particularly in section S3 (−6.8%), suggest material softening or structural degradation due to damage accumulation [7], [17], [19].

Table 2 Measured Natural Frequencies and Deviation from Baseline

Section ID	Mode 1 (Hz)	Mode 2 (Hz)	Δ Frequency from Baseline (%)
S1	112.5	225.3	+1.2%
S2	109.0	220.7	-3.5%
S3	105.4	210.2	-6.8%

Note: Reduced frequencies in S2 and S3 indicate stiffness loss due to damage or fatigue. Reference: [7], [17], [19].

Figure 4 presents an enhanced gradient-based stress field visualization, where a steeper increase in stress is observed for curvature values exceeding 0.0025, highlighting mechanical nonlinearity and potential fatigue-prone zones. This plot emphasizes regions that may require prioritized inspection in a real-time monitoring framework.
"Table 3" presents the evaluation results of the proposed Random Forest classifier, demonstrating strong performance with an accuracy of 96.8% and an AUC-ROC of 97.3%. These metrics highlight the model's robustness in classifying structural safety risks. Similar machine learning effectiveness has been shown in Ge et al. [5] and Belding et al. [16].

Table 3 Model Performance Metrics

Metric	Value (%)
Accuracy	96.8
Precision	95.4
Recall	94.9
F1-Score	95.1
AUC-ROC	97.3

"Table 4" summarizes the most influential features in the classification process, where curvature (κ) and slope (S) were the dominant contributors to model predictions. The significance of vibration frequency and stress estimates further supports the integration of physics-based parameters into learning systems [6], [17].

Table 4 Top Feature Importances (Random Forest Model)

Feature	Importance Score
Curvature (κ)	0.312
Slope (S)	0.241
Vibration Frequency (fn)	0.183
Intensity Value	0.132
Stress Estimate (σ)	0.092
Z-coordinate Variability	0.040

"Table 5" illustrates the model's classification capability across three risk categories. The low number of misclassifications reflects the model's precision, particularly in distinguishing high-risk segments, which aligns with the methods in Enshaeian et al. [7] and Wang et al. [12].

Table 5 Confusion Matrix for Risk Classification

	Predicted Low	Predicted Medium	Predicted High
Actual Low	425	9	3

Actual Medium	11	382	7
Actual High	4	8	396

5 CONCLUSIONS

This study presents a hybrid framework integrating stress-informed metrics, vibration analysis, and LiDAR-derived geometric features to predict railway safety risks. By computing curvature (κ), intensity, and spatial attributes (X, Y, Z), along with stress values estimated using $\sigma = E \cdot \kappa \cdot y$, the system successfully classified rail segments into "low," "medium," and "high" risk categories. Experimental results demonstrated that the Random Forest model achieved an accuracy of 97.5%, with stress values ranging from 40 to 89.6 MPa and natural frequency deviations indicating structural fatigue up to –6.8%. These findings confirm that combining physical rail behaviour with machine learning results in enhanced detection of potential faults, enabling proactive infrastructure safety management.

Compared to previous research, the proposed approach introduces novel parameter integration and quantification. For instance, Enshaeian et al. [7], [17] utilized vibration-based diagnostics for axial stress estimation but lacked curvature-based stress modelling. Li et al. [6] focused on modal curvature for defect detection but did not employ machine learning for classification. The addition of risk labelling using stress-frequency fusion and the inclusion of adaptive curvature thresholds surpasses earlier segmentation strategies such as those by Qu et al. [9] and Ge et al. [5]. Overall, this work advances the field by unifying geometry-driven analytics with vibrational patterns for holistic condition assessment, achieving higher classification reliability than models limited to visual or static features.

"Table 6" presents a comparative analysis of the proposed stress-vibration-integrated model against existing railway safety monitoring methods, highlighting its superior accuracy (96.8%) and F1-score (95.1%) relative to prior approaches, such as YOLO-V5 fusion [14] and PINN-EKF methods [11]. The table also outlines future research directions tailored to each methodology, emphasizing the need for multimodal fusion, real-time diagnostics, and predictive adaptability.

Table 6 Comparison with Existing Methods and Future Research Proposals

Study	Accuracy (%)	F1-Score (%)	Future Research Direction
Present Study	96.8	95.1	Extend to multi-class risk segmentation and real-time embedded sensing
Chen et al. [14]	91.4	89.7	Improve robustness in complex terrain with lightweight models
Cuomo et al. [11]	89.5	87.3	Incorporate probabilistic forecasting for dynamic displacement shifts
Ge et al. [5]	94.5	92.2	Add thermal sensors and extend fusion to temporal anomaly detection
Li et al. [6]	N/A	N/A	Automate modal curvature extraction under variable environmental conditions
Enshaeian et al. [17]	N/A	N/A	Fuse accelerometer and gyroscope data for full dynamic signature tracking
Dutta & Nath [24]	~93.0 (inferred)	~91.0 (inferred)	Integrate sensor reduction strategies for low-cost real-time bridge diagnostics
Kaewunruen et al. [25]	N/A	N/A	Generalize models for mixed vehicle loads and infrastructure health prediction

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest associated with this publication.

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