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Innovative monitoring of railway tunnel deterioration using vibration analysis, LiDAR imaging, and drone technology

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ABSTRACT: The accelerating impacts of climate change pose significant challenges to the safety of underground transport infrastructure. Rising temperatures, increased precipitation, and extreme weather events exacerbate structural vulnerabilities, highlighting the urgent need for innovative monitoring solutions. This study presents an integrated approach to monitoring deterioration in railway tunnels subject to climate change through advanced vibration analysis and LiDAR-based imaging. Vibration data collected using smartphone-based sensors were tested in laboratory conditions and compared with those from commercial sensors, demonstrating promising results in detecting the dynamic responses of tunnel linings to passing trains. Concurrently, the LiDAR capabilities of iPhones were evaluated in an abandoned tunnel with similar characteristics, followed by 3D reconstructions and damage detection within the active Kent tunnel in Cork, Ireland. Machine Learning techniques are being implemented to automatically detect critical damage parameters such as spalling and leakage on shotcrete linings affected by water infiltration. For this purpose, images have been meticulously annotated using Label Studio, a versatile open-source tool, creating a high-quality dataset. YOLOv8 models are then trained on these annotations to achieve automatic segmentation and classification of damage areas, aiming to support faster and more objective assessments of tunnel conditions. Additionally, a custom-built DIY drone system equipped with high-resolution cameras and LiDAR sensors has been assembled to capture detailed visual and spatial data within tunnels. This drone aims to support ongoing monitoring efforts by enabling efficient inspections in complex underground environments. This research highlights the potential of combining vibration analysis, LiDAR imaging, and drone technology to provide a robust framework for proactive tunnel health monitoring under climate change impacts.

KEYWORDS: Climate change, Tunnel monitoring, Vibration analysis, LiDAR imaging, Machine Learning, Drone inspection, Shotcrete damage detection, YOLOv8, Smartphone sensors.

1 INTRODUCTION

The accelerating impacts of climate change pose significant challenges to the safety and durability of underground transport infrastructure, particularly railway tunnels. Rising temperatures, increased precipitation, and extreme weather events (EWEs) exacerbate structural vulnerabilities by promoting moisture infiltration, thermal stresses, and deterioration of tunnel linings (Pantoja Porro et al., 2025). These effects can lead to damage types such as spalling, cracking, and leakage, which threaten tunnel integrity and operational safety (Frenelus et al., 2021). Early detection of such deterioration is critical to prevent costly repairs and service disruptions. However, traditional inspection methods rely on visual surveys are often subjective, time-consuming, and limited by difficult access conditions, emphasizing the need for innovative, reliable, and efficient monitoring techniques (Musarat et al., 2024).

This research develops an integrated monitoring approach that combines vibration analysis with smartphone sensors, LiDAR-based imaging, and Machine Learning (ML) for automated damage detection in train tunnels. Vibration data collected during laboratory and field conditions offer insights into dynamic tunnel responses to passing trains, while LiDAR imaging allows detailed 3D structural assessment. Supporting these technologies, a custom-built drone fitted with high-resolution cameras and LiDAR sensors has been developed to carry out detailed inspections in GPS-denied underground environments. Together, these innovative tools create a robust framework to improve tunnel health monitoring amid climate-induced challenges.

2 METHODOLOGY

2.1 *Vibration monitoring using smartphone sensors*

This study employs a smartphone-based accelerometer sensor to monitor vibrations within the Kent railway tunnel, focusing on dynamic structural responses induced by passing trains and track changes. The use of smartphones as vibration monitoring tools offers an accessible, cost-effective alternative to conventional industrial sensors, enabling dense spatial coverage and continuous data collection (Sony et al., 2019).

2.2 *Sensor validation and laboratory testing*

Prior to field deployment, the smartphone accelerometer was rigorously tested in a controlled laboratory environment against a high-precision commercial accelerometer sensor. Both devices were subject to identical vibration inputs on a test rig to evaluate the smartphone's performance in terms of accuracy, sensitivity, and noise characteristics.

Results demonstrated a strong correlation between the smartphone and commercial sensor data, validating the smartphone's capability to reliably capture vibration events within the frequency and amplitude ranges relevant to tunnel monitoring. This validation underpins the use of smartphones as practical monitoring tools for railway tunnel structural health assessment.

2.3 *Sensor deployment and data acquisition*

Two smartphones were installed at distinct locations within the tunnel, one fixed on the shotcrete lining and the other on the brick lining section. These locations were selected to compare the vibration responses of different tunnel lining materials under operational conditions.

The accelerometers recorded triaxial acceleration data continuously over multiple days, capturing a variety of vibration events such as train passages and track switching operations. However, exact timestamps for train passing and track changes were not directly available, requiring post-processing to differentiate these events.

2.4 *Data processing and feature extraction*

The vibration analysis focused on the vertical axis (Z-axis) acceleration, as it presented the most significant dynamic response from the tunnel lining. The raw acceleration signal was transformed into an amplitude signal by taking the absolute value of the Z-axis acceleration:

$$Magnitude = |Z| \tag{1}$$

To identify significant vibration events, statistical thresholds were established using a multiple standard deviation method. The mean (μ) and standard deviation (σ) of the amplitude signal were calculated, with upper and lower thresholds defined as:

$$Upper\ threshold = \mu + \kappa + \sigma \tag{2}$$

$$Lower\ threshold = \mu - \kappa + \sigma \tag{3}$$

where κ is a tuning parameter selected to balance sensitivity and noise rejection.

Figure 1 illustrates the vibration magnitude data with the detected train passing events highlighted. The upper and lower threshold limits used for event detection are shown with dashed lines, while detected event periods are shaded in green lines.

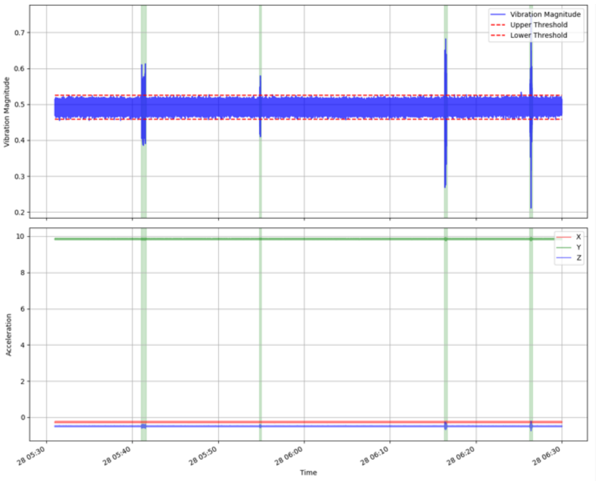

Figure 1. Vibration data with detected train passing events

Vibration points exceeding these thresholds were aggregated into continuous event segments based on temporal proximity, representing individual vibration occurrences such as train passing or track changes.

For each event segment, several statistical features were extracted, including:

- Duration $T = t_{end} - t_{start}$
- Peak amplitude (maximum magnitude)
- Root mean square (RMS) amplitude
- Mean amplitude

These features enabled quantitative characterization of vibration events and supported subsequent classification tasks.

2.5 *Event classification*

Using the extracted features, an unsupervised classification approach based on K-Means clustering (κ=2) was implemented following Z-score normalization of the data. This clustering differentiated two main vibration event types:

- Train passing events
- Track change events

2.6 *LiDAR imaging in tunnel environments*

The LiDAR technology embedded in iPhone provides an innovative and accessible tool for monitoring railway tunnels, enabling rapid and precise capture of three-dimensional data (McDonald et al., 2022). This LiDAR sensor emits laser pulses to measure distances and generate high-resolution 3D point clouds, facilitating the visual and structural inspection of complex surfaces such as tunnel linings (Kaartinen et al., 2022). However, it has inherent limitations, including reduced accuracy on highly reflective surfaces or under poor visibility conditions, which must be considered when deploying it in underground environments (Zhang et al., 2023).

Table 1. Technical specifications of iPhone 12 and iPhone 16 Pro LiDAR scanners used in tunnel scanning.

Specification	iPhone 12	iPhone 16 Pro
LiDAR Range	Up to 5 meters	Up to 10 meters
Spatial Resolution	Approx. 1.5 mm	Approx. 1.0 mm
Field of View (FoV)	120 degrees	130 degrees
Scan Rate (points per sec)	~ 300,000 points/sec	~ 500,000 points/sec
Sensor Type	Time-of-Flight (ToF)	ToF with improved sensitivity
Operating Environment	Indoor/Outdoor (limited range)	Indoor/Outdoor (extended range)
Typical Application	AR, Spatial Mapping	AR, Spatial Mapping, Industrial inspections

2.7 *Field test and data acquisition*

Field tests were conducted in an abandoned tunnel located in Innishannon, Cork (Ireland), with characteristics similar to the active Kent tunnel located in Cork (Ireland) to evaluate the feasibility of using iPhone LiDAR in tunnel monitoring. These monitoring tests validated the sensor's capability to capture the internal geometry of the tunnel and detect surface irregularities that may indicate structural deterioration (Figures 2 and 3). The tunnel environment presents challenges such as limited lighting, humidity, and dust, which affect data quality and require mitigation strategies during data acquisition (Yang et al., 2022).

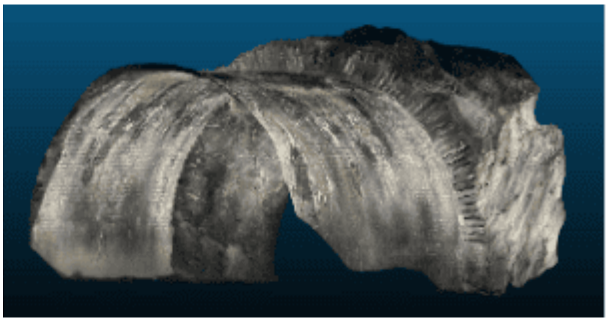

Figure 2. Tunnel cross-section captured by iPhone LiDAR

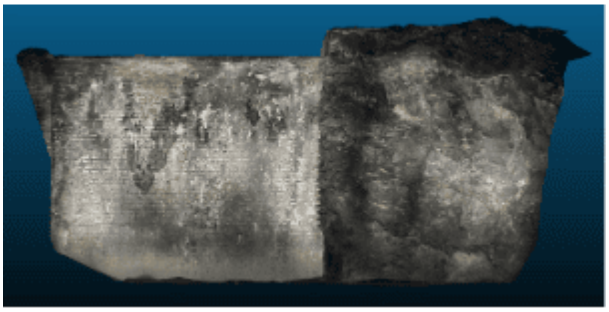

Figure 3. Longitudinal section of the tunnel from LiDAR data

2.8 *Data processing and damage identification*

The LiDAR data was initially captured using the 3D Scanner App, which enabled efficient real-time acquisition and visualization of high-density point clouds within the tunnel environment. (Camara et al., 2025) After data acquisition, sophisticated 3D reconstruction methods were employed to convert the point clouds into precise digital models. This processing facilitated the accurate identification of structural damages such as cracks, spalling, and deformations in the tunnel lining, providing a quantitative basis for comprehensive structural assessment.

Figure 4 shows the longitudinal section of the Kent tunnel generated from the LiDAR point cloud. Meanwhile, Figure 5 provides a zoomed-in view of a selected area highlighting multiple water leakage areas within the tunnel lining, which are critical for targeted maintenance and repair.

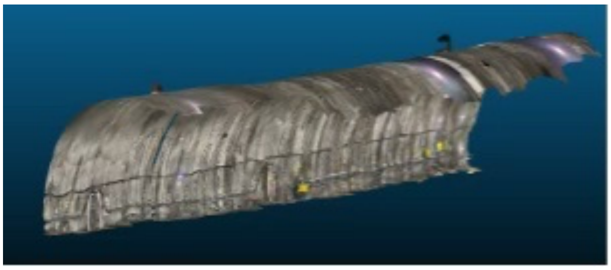

Figure 4. Longitudinal section of the Kent tunnel from LiDAR data

Figure 5. Figure 1. Zoomed detail of water leakage detected in the tunnel lining.

2.9 *Limitations and challenges*

Nonetheless, LiDAR use in tunnels has limitations, including the need for multiple scans from various positions to cover extensive areas, reliance on controlled environmental conditions, and intensive computational resources to process large datasets (Fekete et al., 2010). Despite these challenges, iPhone LiDAR technology represents a significant step forward in more efficient and accurate inspections of underground infrastructure affected by climate change (Mizutani and Iwai, 2024).

2.10 *Machine Learning for automated damage detection*

The complexity and scale of tunnel infrastructure inspection demand advanced tools that can enhance the speed and accuracy of damage identification. ML offers a powerful solution to automate the detection and classification of structural defects, reducing the reliance on time-consuming manual inspections and subjective human judgment (Taheri and Salimi Beni, 2025). In this study, ML techniques are applied to identify critical damages such as spalling and water leakage on shotcrete linings, which are common issues that compromise tunnel integrity and safety.

2.11 *Dataset preparation and annotation*

Figure 6 illustrates the output of the trained YOLOv8m-seg model, showing automatic detection and contouring of water leakages in the tunnel sections. The model effectively identifies and delineates areas of water infiltration, demonstrating its capability for precise damage segmentation within challenging underground environments.

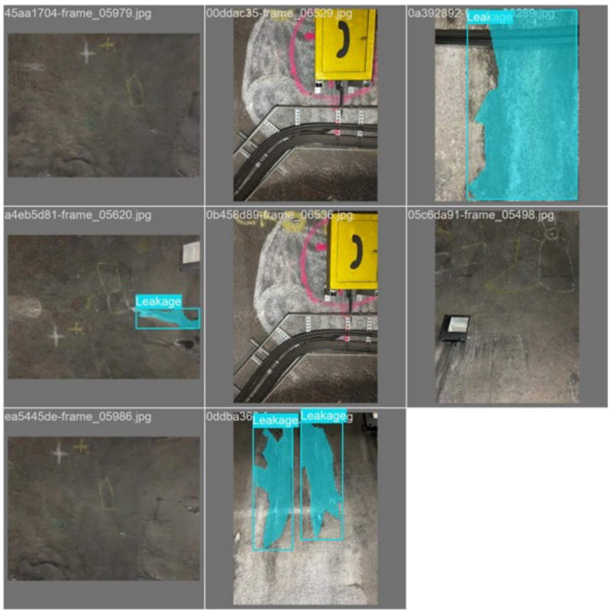

Figure 6. YOLOv8m-seg detection of water leakages in tunnel sections

To develop an effective ML-based inspection system, a high-quality dataset was prepared through meticulous manual annotation using Label Studio, an open-source annotation tool.

This involved labelling hundreds of tunnel images with precise masks that delineate the regions exhibiting spalling and leakage damage. The annotated dataset was then split into training, validation and testing subsets to ensure robust model evaluation and to prevent overfitting.

2.12 *Model choice and training strategy*

YOLOv8, a state-of-the-art deep learning architecture for object detection and instance segmentation, was selected for this task due to its balance of accuracy and inference speed (Safaldin et al., 2024). The models were trained on the labelled dataset using augmentation and hyperparameter tuning to improve model generalization across various tunnel conditions. Training parameters and validation performance metrics, including precision, recall, mAP50, and mAP50-95, are detailed in Table 2.

Table 2. Summary of training configuration and performance metrics

Parameter	Value
Model	YOLOv8m-seg
Epochs	50
Batch size	4
Image size	640 x 640 px
Hardware	CPU
Final total loss	~2.1
Box loss	0.57
Segmentation loss	0.91
Classification loss	0.67

Precision	0.44
Recall	~0.37
mAP50 (bounding boxes)	0.54
mAP50 (masks)	0.50
mAP50-95 (detection)	~0.24

Performance was evaluated using standard metrics such as precision, recall, mean Average Precision at IoU 0.5 (mAP50), and mAP across multiple IoU thresholds (mAP50-95).

Initial results indicate promising capabilities of the YOLOv8 models to accurately segment and classify damaged areas within tunnel images, with mAP values showing steady improvement after multiple training epochs. However, challenges remain due to varying lighting conditions, damaged appearances, and image quality typical of underground environments.

2.13 *DIY Drone System for tunnel inspection*

To complement the tunnel monitoring system, a custom-built (DIY) drone has been developed specifically for inspection in underground environments, where navigation and control pose particular challenges.

2.14 *Drone design and main components*

The drone features a compact and robust frame designed to manoeuvre efficiently in confined spaces such as railway tunnels. Its primary components include:

A high-resolution camera (GoPro Hero 11) for capturing detailed images of tunnel lining conditions
A LiDAR sensor (Benewake TFmini-S) for generating precise 3D spatial data of the tunnel interior.
A Pixhawk flight controller, chosen for its versatility and wide support in autonomous drone applications.

Table 3 below summarizes the technical specifications of the main components:

Table 3. Drone components and key specifications

Component	Model	Key Specification
Frame	ReadyToSky ZD550	Lightweight carbon fibre, 550 mm diagonal
Camera	GoPro Hero 11	5.3k video, 23 MP photos, wide-angle lens
LiDAR Sensor	BenewakeT Fmini-S	Range: 0.1 -12 m, accuracy ±5 cm
Flight Controller	Pixhawk 4	32-bit ARM Cortex M7, multiple sensors
Power Supply	LiPo Battery 4S	14.8 V, 5200 mAh capacity
Frame	ReadyToSky ZD550	Lightweight carbon fibre, 550 mm diagonal

2.15 *Navigation and control in GPS-denied environments*

Operating in tunnels prevents the use of GPS; thus, the navigation relies on sensor fusion of inertial measurement units (IMUs), LiDAR data, and computer vision algorithms. Open-source software such as PX4 autopilot firmware manages flight control, while ROS (Robot Operating System) enables integration of sensor data and real-time mapping (SLAM) (Zhang et al., 2023; da Silva, 2024). The key software components and their functions used in this system are summarized in Table 4.

Table 4. Software components and functions

Software	Purpose	Reason
PX4 Autopilot	Flight Control	Open-source, customizable
ROS	Sensor integration and mapping	Real-time processing, GPS-denied
QGround Control	Mission planning	User-friendly interface
OpenCV	Image processing	Real-time vision tasks
Python	Scripting and Automation	Flexible and widely used

2.16 *System integration and assembly*

The drone is assembled by integrating all hardware components and configuring software modules to operate harmoniously. Its modular design supports future upgrades and maintenance and allows synchronization with other monitoring platforms used in this research.

2.17 *Planned functionalities and current testing status*

Expected functionalities include automated image and LiDAR data acquisition with spatial referencing, generation of 3D tunnel models for structural analysis, and autonomous waypoint navigation along predefined routes. The drone is currently assembled and initial calibration phase, preparing for field validation. Data collected from the drone will be integrated with wireless sensor networks (WSNs) outputs and smartphone-based vibration monitoring to deliver a comprehensive, multi-source assessment of tunnel health.

3 RESULTS

3.1 *Tunnel damage detection using YOLOv8*

The machine learning-based damage detection system is based on a large dataset of approximately 12,000 images of tunnel lining captured with an iPhone LiDAR camera, meticulously labelled for two main damage types: spalling and leakage. However, for initial experiments and model benchmarking, a smaller subset of 1,262 images was used to train and validate the first two models. This smaller dataset was slit into training (70%), validation (15%), and testing (15%) subsets to ensure robust evaluation of model accuracy and performance.

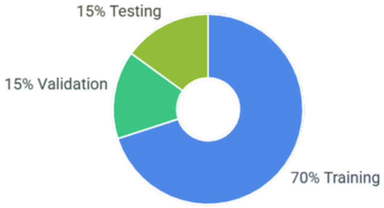

Figure 7. Data distribution for machine learning model

Two YOLOv8 segmentation models were tested: the lightweight YOLOv8n-seg and the more complex YOLOv8m-seg. The medium model (YOLOv8m) demonstrated better balance in performance, achieving higher precision (~53%) compared to the nano model (~33%), although with a slightly lower recall (37% vs 51%). The mean Average Precision at IoU (mAP50) for the YOLOv8m-seg model indicated a reasonable segmentation capability, with a mask mAP50 values of around 0.23 to 0.37 during validation, signalling that the model was able to identify damage areas with moderate confidence.

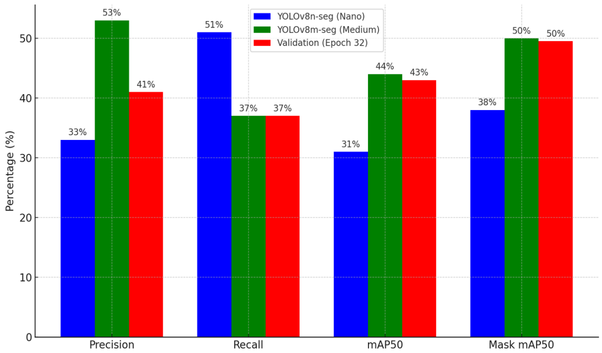

Figure 8. Comparison of YOLOv8 Segmentation Model Performance

While these results are promising, there remains room for improvement, particularly to increase the precision and recall values for more confident damage detection. Future work on enhancing dataset quality, balancing class representation, optimizing hyperparameters, and exploring ensemble methods to reduce false positives and better capture damage boundaries. Subsequent training stages will leverage the full 12,000-image dataset for further enhance model generalization and detection capabilities.

3.2 *Vibration monitoring results*

The smartphone successfully captured vibration events within the Kent tunnel, with clear differentiation between train passing and track change events based on the extracted statistical features.

Figure 9 presents box plots comparing the duration, average magnitude, and RMS amplitude of vibration events across two different tunnel lining materials: shotcrete and brick. The results show that events recorded on brick lining tend to have longer durations, higher average magnitudes, and greater RMS values compared to those on shotcrete. These differences highlight how structural responses vary with lining material, with brick sections experiencing more intense vibrations.

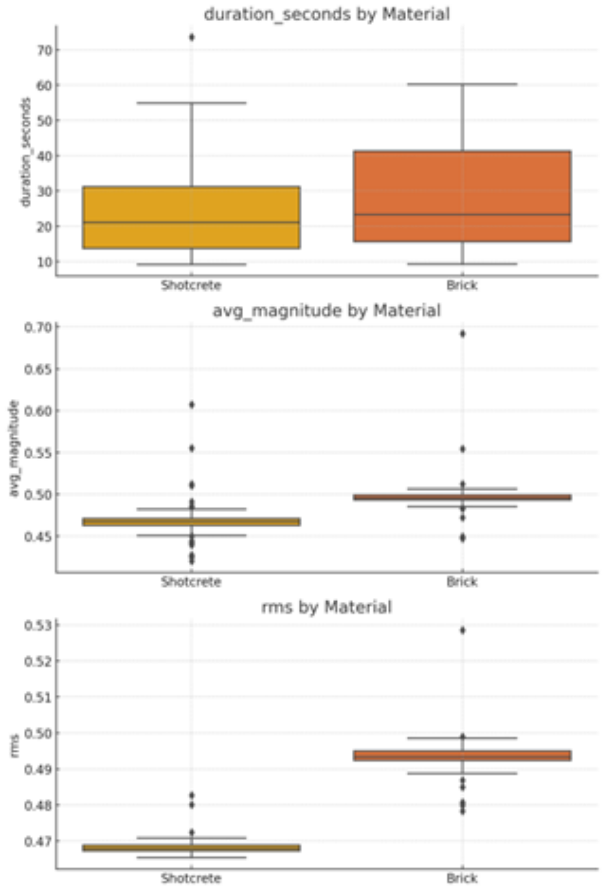

Figure 9. Comparison of vibration even features by tunnel lining material: duration (seconds), average magnitude, and RMS amplitude

Using supervised learning classifiers, six distinct algorithms were evaluated for their ability to distinguish between normal and abnormal vibration events recorded by smartphone sensors. These included Random Forest, XGBoost, Support Vector Machine (SVM), Multi-layer Perceptron (MLP), optimized MLP with hyperparameter tuning (MLP+Grid), and K-Nearest Neighbors (KNN). All models were trained on the same input features—comprising event duration, amplitude metrics, and point counts—and assessed using standard ROC-AUC metrics.

The optimized MLP model achieved the highest AUC of 0.89, as shown Figure 10, followed closely by the default MLP (AUC = 0.86) and Random Forest (AUC = 0.85). XGBoost and SVM also demonstrated strong performance with AUC values of 0.83 and 0.82 respectively, while KNN lagged with an AUC of 0.76. This variation highlights the importance of model selection and hyperparameter tuning in vibration classification tasks, especially under limited sample conditions.

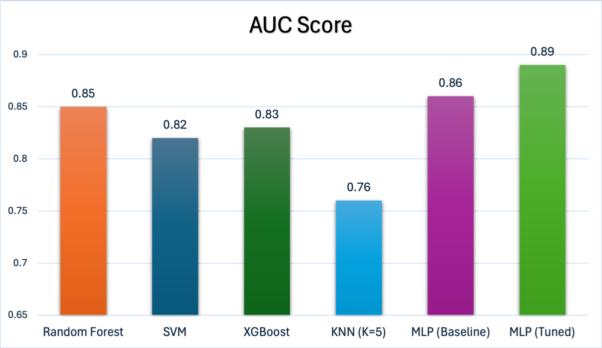

Figure 10. AUC scores for the six evaluated models, with tuned MLP performing best and KNN lowest

The ROC curves further illustrate that neural network-based models (MLP) tend to generalize better across the classification boundary, as indicated by the steeper TPR-FPR trajectories. Meanwhile, the ensemble-based Random Forest model not only yielded competitive accuracy but also provided insights into feature relevance. Feature importance analysis revealed that event duration and point count were the most predictive variables, followed by amplitude and maximum magnitude, suggesting that both temporal and energetic characteristics of vibration events are critical for classification.

Collectively, these findings confirm the suitability of supervised learning approaches for post-processing smartphone-based vibration data. Compared with earlier unsupervised methods (e.g., K-Means), supervised models deliver more reliable event classification and probabilistic predictions, enabling robust anomaly detection and contributing to data-driven tunnel health monitoring strategies.

4 CONCLUSIONS

This study demonstrates the potential of integrating multiple innovative technologies for effective monitoring of deterioration in railway tunnels. The smartphone-based vibration monitoring system was validated against a commercial sensor and successfully differentiated key dynamic events such as train passages and track changes, revealing material-dependent vibration responses. This cost-effective approach enables dense spatial coverage and continuous data acquisition in operational tunnels.

Simultaneously, iPhone LiDAR technology provided a detailed 3D reconstruction of the tunnel geometry and facilitated accurate detection of structural damage, including spalling and water leakages, despite the challenges posed by harsh underground conditions. The application of state-of-the-art Machine Learning, particularly YOLOv8 segmentation models trained on meticulously annotated datasets, demonstrated promising results in automated damage identification, paving the way for more objective and efficient tunnel inspections.

Furthermore, the development of a custom-built drone equipped with high-resolution imaging and LiDAR sensors adds a versatile tool for comprehensive tunnel health assessment in GPS-denied environments, complementing stationary sensor networks and smartphone monitoring.

Overall, the integrated framework combining vibration analysis, LiDAR imaging, ML-based damage detection, and autonomous drone inspection presents a robust, scalable, and cost-effective strategy to enhance the resilience and safety of railway tunnels under climate change impacts. Future work will focus on refining ML model accuracy, expanding monitoring coverage, and integrating multi-source data for predictive maintenance and early warning systems.

5 ACKNWOLEGEMENTS

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