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Reliable Beam Tracking on High-Altitude Platform for Millimetre WaveHigh-Speed Railway

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Abstract- High-speed railway (HSR) systems require reliable and high-capacity wireless communication to support passenger services, operational control, and safety-critical applications. However, maintaining uninterrupted connectivity for trains operating at speeds exceeding 300 km/h remains challenging, particularly for millimeter-wave (mmWave) communication due to severe path loss, signal blockage, and frequent beam misalignment. Conventional ground-based communication infrastructures often fail to provide consistent performance in such highly dynamic environments. This paper presents an integrated intelligent framework titled "Reliable Beam Tracking on High-Altitude Platform for Millimetre Wave High-Speed Railway", which leverages High-Altitude Platforms (HAPs) and data-driven prediction techniques to enhance communication reliability. A supervised machine learning model is developed to predict mmWave beam reliability using key railway operational and geographical parameters such as train speed, population density, track information, and location attributes. In parallel, a deep learning-based Convolutional Neural Network (CNN) is employed to automatically detect structural defects in railway beams from image data, reducing reliance on manual inspections. Experimental results demonstrate that the proposed beam reliability prediction model achieves high classification accuracy, while the CNN-based defect detection model effectively identifies defective railway structures with strong confidence. The integration of both modules into a unified Flask-based web platform enables real-time prediction, automated infrastructure monitoring, and interactive data visualization. The proposed system offers a practical and scalable solution for improving communication stability and infrastructure safety in next-generation high-speed railway networks.

I. INTRODUCTION

High-speed railway (HSR) systems have emerged as a vital mode of transportation due to their efficiency, safety, and environmental benefits. With train speeds exceeding 300 km/h, the demand for reliable, high-capacity wireless communication has become increasingly important for passenger services, train control, and real-time monitoring. However, ensuring uninterrupted connectivity in such high-mobility environments remains a significant technical challenge for conventional communication infrastructures.

Millimeter-wave (mmWave) communication has gained considerable attention as a key technology for next-generation wireless networks because of its ability to support extremely high data rates and large bandwidth. Despite these advantages, mmWave communication is highly sensitive to signal blockage, atmospheric attenuation, and beam misalignment. These challenges are further intensified in high-speed railway scenarios, where rapid train movement causes frequent changes in position, making accurate beam tracking difficult.

To overcome the limitations of terrestrial base stations, High-Altitude Platforms (HAPs) positioned in the stratosphere have been proposed as an effective solution for railway communication. HAPs offer wide-area coverage, improved line-of-sight connectivity, and reduced handover frequency compared to ground-based systems. However, maintaining reliable beam alignment between fast-moving trains and HAP-based mmWave links requires intelligent prediction and tracking mechanisms.

In addition to communication challenges, the physical integrity of railway infrastructure is equally critical. Railway beams and supporting structures are subjected to continuous mechanical stress and environmental effects, leading to potential defects over time. Traditional manual inspection methods are time-consuming, costly, and prone to human error, highlighting the need for automated and intelligent defect detection systems.

This project proposes an integrated solution titled "Reliable Beam Tracking on High-Altitude Platform for Millimetre Wave High-Speed Railway", which combines machine learning techniques for beam reliability prediction with deep learning-based image analysis for railway beam defect detection. A web-based platform is developed to provide real-time predictions, infrastructure monitoring, and data visualization, enabling railway authorities to enhance communication reliability and operational safety in high-speed railway networks.

II. PROBLEM STATEMENT

High-speed railway (HSR) systems demand reliable, low-latency, and high-capacity wireless communication to support passenger connectivity, train control, and safety-critical applications. With train operating speeds exceeding 300 km/h, maintaining stable communication links becomes increasingly challenging due to rapid mobility, frequent handovers, and dynamic channel conditions. Traditional ground-based cellular communication infrastructures are often unable to provide consistent performance under such extreme mobility scenarios.

Millimeter-wave (mmWave) communication has emerged as a promising solution for next-generation railway networks because of its large available bandwidth and ability to support high data rates. However, mmWave signals are highly susceptible to severe path loss, signal blockage, atmospheric attenuation, and frequent beam misalignment. These limitations are significantly amplified in high-speed railway environments, where fast-moving trains cause rapid changes in position and orientation, resulting in unstable beam alignment and degraded link quality.

High-Altitude Platforms (HAPs) positioned in the stratosphere offer an alternative communication architecture with wide-area coverage, improved line-of-sight connectivity, and reduced handover frequency compared to terrestrial base stations. Despite these advantages, ensuring continuous and accurate beam alignment between HAP-based mmWave transmitters and high-speed trains remains a critical technical challenge. Conventional beam tracking techniques are often reactive and struggle to adapt quickly to highly dynamic railway environments.

In addition to communication challenges, the physical integrity of railway infrastructure plays a vital role in ensuring safe and uninterrupted railway operations. Railway beams and supporting structures are continuously exposed to mechanical stress, vibration, and environmental factors, leading to gradual deterioration and potential structural defects. Existing manual inspection methods are time-consuming, labor-intensive, and prone to human error, making them unsuitable for large-scale and frequent monitoring.

Therefore, the core problem addressed in this work is the lack of an intelligent, integrated system capable of (i) proactively predicting the reliability of mmWave beam communication in HAP-assisted high-speed railway environments and (ii) automatically detecting structural defects in railway beams using data-driven techniques. Addressing these challenges is essential to achieving reliable communication, improved infrastructure safety, and enhanced operational efficiency in next-generation high-speed railway systems.

III. OBJECTIVES

The primary objective of this research is to design and develop an intelligent and integrated framework that enhances communication reliability and infrastructure safety in high-speed railway (HSR) systems using advanced data-driven techniques. The specific objectives of the proposed work are as follows:

1. To analyze the challenges associated with millimeter-wave (mmWave) communication in high-speed railway environments, particularly issues related to beam misalignment, signal attenuation, and high mobility.
2. To develop a machine learning–based model for predicting the reliability of mmWave beam communication in High-Altitude Platform (HAP)-assisted railway networks using key operational and geographical parameters.
3. To design and implement a deep learning–based Convolutional Neural Network (CNN) for automated detection of structural defects in railway beam components from image data.
4. To integrate the beam reliability prediction and defect detection modules into a unified web-based

platform that supports real-time prediction, monitoring, and visualization.
5. To evaluate the performance of the proposed models using appropriate metrics such as accuracy, confusion matrix, and response time, and to analyze their effectiveness in practical high-speed railway scenarios.
6. To provide intelligent decision-support recommendations that assist railway authorities in improving communication stability and prioritizing infrastructure maintenance activities.

IV. SCOPE OF THE STUDY

The scope of this study is focused on the design, implementation, and evaluation of an intelligent and integrated framework for improving communication reliability and infrastructure safety in high-speed railway (HSR) systems. The proposed work primarily addresses challenges related to millimeter-wave (mmWave) communication and railway beam condition monitoring in High-Altitude Platform (HAP)-assisted environments.

This study considers the prediction of mmWave beam reliability using machine learning techniques based on selected railway operational and geographical parameters, including train speed, population density, track information, number of trains, and location attributes. The scope is limited to classification-based beam reliability assessment, where communication links are categorized as reliable or not reliable under given operating conditions.

The infrastructure monitoring component of this work is restricted to automated detection of structural defects in railway beam components using image-based deep learning methods. The Convolutional Neural Network (CNN) model focuses on identifying the presence or absence of defects in beam structures based on visual features extracted from labeled image datasets. Detailed defect localization, severity estimation, or real-time video-based inspection is not included within the current scope.

The proposed system is implemented as a web-based application using the Flask framework, providing real-time prediction, automated defect detection, and interactive data visualization. The scope of deployment is limited to experimental evaluation and simulated operational scenarios, without direct integration into live railway communication networks or safety-critical control systems.

V. EXISTING SYSTEM

Existing communication and monitoring systems in high-speed railway (HSR) environments primarily rely on conventional ground-based wireless infrastructure and manual or semi-automated inspection techniques. Terrestrial cellular networks such as LTE and early 5G deployments are commonly used to support passenger connectivity and railway operational communication. These systems depend on fixed base stations placed along railway tracks, requiring frequent handovers as trains move at very high speeds.

In high-mobility scenarios, especially at speeds exceeding 300 km/h, ground-based communication systems experience significant performance degradation due to rapid handovers, Doppler effects, and frequent signal blockage caused by terrain and infrastructure. Millimeter-wave (mmWave) communication, although capable of providing high data rates, suffers from severe path loss and beam misalignment when applied using traditional terrestrial architectures. Existing beam tracking methods are largely reactive and struggle to maintain stable alignment under highly dynamic railway conditions.

To address coverage limitations, some existing approaches employ satellite-based or relay-assisted communication systems. While these methods offer wider coverage, they often introduce higher latency, limited bandwidth, and increased operational costs. Moreover, most existing communication solutions focus solely on maintaining connectivity and do not incorporate intelligent prediction mechanisms to proactively assess beam reliability before link degradation occurs.

In terms of infrastructure monitoring, existing railway systems primarily rely on scheduled manual inspections and sensor-based monitoring techniques. Manual inspection processes are labor-intensive, time-consuming, and prone to human error, making them unsuitable for frequent and large-scale monitoring of railway beam structures. Although some automated solutions using cameras and basic image processing techniques have been introduced, they often lack robustness and accuracy, particularly under varying environmental conditions.

VI. PROPOSED SYSTEM

The proposed system introduces an intelligent and integrated framework designed to enhance communication reliability and infrastructure safety in high-speed railway (HSR) environments. By combining machine learning–based beam reliability prediction with deep learning–based railway beam defect detection, the system addresses key limitations of existing communication and monitoring approaches in a unified and proactive manner.

A. System Overview

The proposed framework leverages High-Altitude Platforms (HAPs) operating in the stratosphere to support millimeter-wave (mmWave) communication for high-speed trains. Unlike conventional ground-based systems, HAP-assisted communication provides improved line-of-sight connectivity, wider coverage, and reduced handover frequency. To ensure stable communication under high mobility conditions, the system incorporates intelligent prediction mechanisms that assess beam reliability in advance.

In parallel, the framework includes an automated infrastructure monitoring module that evaluates the structural condition of railway beams using image-based deep learning techniques. Both communication reliability prediction and defect detection are integrated into a single web-based decision-support platform, enabling real-time analysis, monitoring, and visualization.

B. Machine Learning–Based Beam Reliability Prediction

To predict the reliability of mmWave beam communication, a supervised machine learning approach is employed. Railway operational and geographical parameters such as train speed, population density, number of tracks, train frequency, and location attributes are used as input features. These features are preprocessed through normalization and encoding before being passed to a Random Forest classifier.

The trained model classifies beam conditions into two categories: Reliable and Not Reliable. This proactive prediction enables railway authorities to anticipate communication degradation and take corrective actions such as adjusting train speed, modifying beam parameters, or planning infrastructure enhancements.

C. Deep Learning–Based Railway Beam Defect Detection

The proposed system incorporates a Convolutional Neural Network (CNN) to automatically detect structural defects in railway beam components. The CNN processes labeled images of railway beams to identify visual anomalies such as cracks, corrosion, and surface deformation. Through convolution and pooling operations, the model extracts discriminative features, which are then used to classify beam conditions as Defective or Non-Defective.

This automated approach significantly reduces the dependency on manual inspection, improves detection accuracy, and enables timely maintenance decisions, thereby enhancing overall railway safety.

D. Integrated Web-Based Decision-Support Platform

Both the beam reliability prediction and defect detection modules are integrated into a unified web-based platform developed using the Flask framework. The platform allows users to input railway route parameters, upload beam images, and receive real-time prediction results. Interactive data visualization and map-based analytics are provided using Plotly and Mapbox to support informed decision-making.

The integrated design ensures seamless interaction between communication reliability assessment and infrastructure monitoring, offering a comprehensive solution for high-speed railway management.

E. Advantages of the Proposed System

The proposed system offers several key advantages over existing approaches:

- Proactive prediction of mmWave beam reliability using data-driven machine learning techniques.
- Automated detection of railway beam defects using deep learning-based image analysis.

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- Reduced reliance on manual inspection and reactive communication management.
- Unified platform combining communication and infrastructure monitoring.
- Improved operational efficiency, communication stability, and infrastructure safety.

VII. LITERATURE SURVEY

High-speed railway (HSR) communication systems have gained significant research attention due to the growing demand for reliable, high-capacity wireless connectivity in high-mobility environments. In particular, millimeter-wave (mmWave) communication has been identified as a key enabling technology for next-generation railway networks because of its large bandwidth and high data rate capabilities. However, maintaining reliable mmWave communication under high-speed conditions remains a challenging research problem.

Wang *et al.* conducted a comprehensive survey on beam training and beam tracking techniques in mmWave communication systems. Their study analyzed fundamental challenges such as severe path loss, narrow beamwidth requirements, and frequent beam misalignment caused by user mobility. The authors highlighted that conventional beam tracking approaches struggle in highly dynamic scenarios and emphasized the need for intelligent and low-latency beam tracking mechanisms, especially for high-speed users such as trains.

Gao *et al.* investigated dynamic mmWave beam tracking techniques specifically for high-speed railway communication scenarios. Their work demonstrated that rapid train movement leads to frequent beam misalignment and increased signaling overhead. The study proposed adaptive beam tracking strategies to improve link stability; however, the approach mainly focused on communication aspects and did not consider predictive data-driven models or infrastructure-related factors.

Zhang *et al.* proposed a predictive beam training sequence design for dynamic mmWave channels using stochastic modeling techniques. Their approach improved beam alignment accuracy under mobility conditions by leveraging temporal channel characteristics. While effective, the method relied heavily on channel state modeling and did not incorporate operational railway parameters such as train density, population distribution, or route characteristics that influence real-world performance.
Recent studies have also explored alternative communication architectures to overcome the limitations of terrestrial base stations. Xing *et al.* examined the design and performance of High-Altitude Platform Stations (HAPS) for wireless communication systems. Their findings showed that HAPS can provide wide-area coverage, improved line-of-sight connectivity, and reduced handover frequency. These advantages make HAPS a promising solution for high-speed railway communication; however, maintaining reliable beam alignment between HAPS and fast-moving trains remains an open research challenge.

In parallel with communication reliability research, railway infrastructure monitoring has emerged as a critical area for improving operational safety. Choi *et al.* applied deep learning-based Fast R-CNN models for rail surface defect detection and demonstrated high accuracy in identifying cracks and surface anomalies. Their work confirmed that convolutional neural networks are effective for automated defect detection compared to traditional image processing methods.

Kumar presented a systematic literature review on railway defect detection techniques, highlighting the transition from manual inspections and classical image processing methods to deep learning-based approaches. The review emphasized that although CNN-based models significantly improve detection accuracy and efficiency, most existing systems operate independently of communication management frameworks.

From the reviewed literature, it is evident that existing research efforts primarily address either mmWave communication reliability or railway infrastructure monitoring as separate problems. There is a lack of integrated systems that combine intelligent beam reliability prediction with automated structural defect detection within a unified decision-support framework. This research gap motivates the proposed work, which aims to integrate machine learning-based communication reliability prediction and deep learning-based infrastructure monitoring to support safer and more reliable high-speed railway operations.

VIII. METHODOLOGY

The methodology of the proposed system focuses on designing an intelligent and integrated framework that ensures reliable millimeter-wave (mmWave) communication and automated railway beam defect detection for high-speed railway systems. The overall approach combines machine learning, deep learning, and web-based technologies to achieve accurate prediction, monitoring, and visualization.

A. Overall System Architecture

The proposed system follows a modular architecture consisting of four major components: data collection and preprocessing, beam reliability prediction, railway beam defect detection, and web-based visualization. Each module operates independently while being seamlessly integrated into a unified platform.

B. Data Collection and Preprocessing

Railway operational and geographical datasets are collected, including parameters such as train speed, population density, number of tracks, number of trains passing or stopping, and geographical coordinates. The collected data is cleaned to remove inconsistencies and missing values. Categorical attributes are converted into numerical form using label encoding, while numerical features are normalized using standard scaling to improve model performance.

C. Beam Reliability Prediction Using Machine Learning

A supervised machine learning approach is employed to predict the reliability of mmWave beam communication. The preprocessed dataset is divided into training and testing sets. A Random Forest classifier is trained using key operational features to classify beam reliability as “Reliable” or “Not Reliable.” The trained model is evaluated using accuracy and confusion matrix metrics. During system operation, user-provided route parameters are processed and passed to the trained model to generate real-time predictions along with actionable suggestions.

D. Railway Beam Defect Detection Using Deep Learning

To ensure infrastructure safety, a deep learning-based Convolutional Neural Network (CNN) is used to detect defects in railway beam structures. Images of railway beams are collected and labeled as defective or non-defective. Each image is resized, normalized, and fed into the CNN model. The model extracts visual features through convolution and pooling layers and classifies the images using fully connected layers. The output includes defect classification and confidence scores.

E. Web-Based Application Development

A web application is developed using the Flask framework to provide a user-friendly interface. The application allows users to input railway parameters for beam reliability prediction, upload images for defect detection, and view prediction results. Interactive data visualization and map-based displays are implemented using Plotly and Mapbox to support exploratory data analysis and route-based insights.

F. Result Generation and Smart Suggestions

Based on the outputs from the machine learning and deep learning models, the system generates intelligent suggestions. For unreliable beam predictions, recommendations such as speed adjustment or infrastructure reinforcement are provided. For detected defects, maintenance and inspection suggestions are displayed to assist railway authorities in decision-making.

IX. SYSTEM DESIGN

The system is designed to provide an intelligent solution for improving communication reliability and infrastructure safety in high-speed railway environments. It integrates machine learning, deep learning, and web technologies into a single platform that supports prediction, monitoring, and visualization.

A. Overall System Architecture

The system follows a modular client–server architecture. Users interact with the system through a web interface, while all prediction and processing tasks are handled on the server side. The main components of the system include data input, beam

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reliability prediction, railway beam defect detection, and result visualization.

Railway operational and geographical data are provided by the user through the web interface. These data are processed by the machine learning module to predict the reliability of millimeter-wave (mmWave) communication beams. At the same time, images of railway beam structures can be uploaded for defect detection using a deep learning model.

B. Beam Reliability Prediction Module

This module is responsible for predicting whether mmWave communication beams will remain reliable under given railway conditions. Inputs such as train speed, population density, number of tracks, and route information are collected and preprocessed. A machine learning model analyzes these inputs and classifies the beam condition as either Reliable or Not Reliable. The output helps railway authorities take preventive actions to maintain stable communication.

C. Railway Beam Defect Detection Module

The defect detection module focuses on identifying structural defects in railway beams. Uploaded beam images are processed using a Convolutional Neural Network (CNN). The model examines visual patterns such as cracks, corrosion, or deformation and classifies the beam as Defective or Non-Defective. This automated process reduces the need for manual inspections and improves safety.

D. Web-Based Interface and Visualization

A web application is developed using the Flask framework to provide an easy-to-use interface. Users can enter railway parameters, upload images, and view prediction results. Data visualization tools are used to display charts and maps, helping users understand railway conditions and communication performance clearly.

E. Data Flow and System Operation

The system operates in a simple flow:

User enters railway operational data or uploads beam images.

Data is preprocessed and sent to the respective prediction models.

Machine learning and deep learning models generate predictions.

Results and suggestions are displayed on the web interface.

This design ensures smooth interaction between different system components and enables real-time monitoring and decision support.

X. IMPLEMENTATION

The implementation of the proposed system focuses on integrating machine learning, deep learning, and web technologies to provide a practical solution for beam reliability prediction and railway beam defect detection in high-speed railway environments. The system is implemented using Python-based tools and frameworks to ensure flexibility, scalability, and ease of deployment.

A. Implementation of Beam Reliability Prediction

The beam reliability prediction module is implemented using supervised machine learning techniques. Railway operational and geographical data are collected and stored in a structured dataset. Key features such as train speed, population density, number of tracks, number of trains, and route location are selected as inputs.

The dataset is preprocessed by handling missing values, encoding categorical variables, and normalizing numerical features. A Random Forest classifier is trained using the processed dataset, as it provides good performance with mixed data types and reduces overfitting. The trained model predicts whether the mmWave communication beam is Reliable or Not Reliable based on user-provided inputs.

B. Implementation of Railway Beam Defect Detection

The railway beam defect detection module is implemented using a Convolutional Neural Network (CNN). A dataset of railway beam images is collected and labeled into two categories: Defective and Non-Defective. Each image is resized and normalized before being passed to the CNN model.

The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. During testing, uploaded beam images are processed by the trained CNN model, which outputs the defect classification along with a confidence score.

C. Web Application Implementation

A web-based application is developed using the Flask framework to integrate both prediction modules into a single platform. The application provides user authentication, data input forms, image upload functionality, and result display pages.

When a user submits railway parameters or uploads an image, the Flask backend processes the request and forwards the data to the appropriate machine learning or deep learning model. The prediction results are then returned to the user in real time.

D. Data Visualization and Result Display

To enhance usability, data visualization tools are integrated into the web application. Charts and graphs are generated to show trends related to train frequency, passenger density, and route characteristics. Map-based visualization is used to display railway routes and location-based insights.

The results from both prediction modules are presented in a clear and understandable format, along with simple suggestions to support decision-making.

E. System Integration and Testing

All modules are integrated and tested to ensure smooth communication between the web interface and backend models. Functional testing is carried out to verify correct data flow, prediction accuracy, and response time. The system successfully handles multiple user requests and provides reliable predictions with minimal delay.

XI. TESTING

Testing was carried out to ensure the correctness, reliability, and performance of the proposed system. Both functional and performance testing techniques were used to validate the machine learning–based beam reliability prediction module and the deep learning–based railway beam defect detection module. For the beam reliability prediction module, test cases were designed using different combinations of railway operational parameters such as train speed, population density, and route information. The predicted outputs were verified against expected results to confirm classification accuracy and consistency. Model evaluation metrics such as accuracy and confusion matrix were used to assess performance.

The railway beam defect detection module was tested using labeled images representing defective and non-defective beam conditions. The classification results were verified to ensure correct defect identification and confidence scores.

The web application was tested for input validation, response time, and result display. Overall system testing confirmed smooth integration, reliable predictions, and efficient operation.

XII. CONCLUSION

This project successfully presents an intelligent and integrated solution for addressing two critical challenges in high-speed railway systems: reliable millimeter-wave (mmWave) communication and efficient railway infrastructure monitoring. By leveraging High-Altitude Platforms (HAPs) along with advanced machine learning and deep learning techniques, the proposed system enhances communication reliability and improves infrastructure safety in high-mobility railway environments.

The machine learning-based beam reliability prediction model effectively analyzes railway operational and geographical parameters to determine the stability of mmWave communication links. The results demonstrate that predictive analytics can significantly reduce beam misalignment issues and assist railway authorities in proactive decision-making. In parallel, the deep learning-based Convolutional Neural Network (CNN) successfully automates the detection of defects in railway beam structures, reducing dependence on manual inspections and minimizing the risk of human error.

The integration of these intelligent modules into a unified Flask-based web platform further strengthens the practical applicability of the system. The platform enables real-time prediction, automated defect detection, and interactive data visualization through an intuitive interface. Overall, the experimental results and analysis confirm that the proposed approach improves operational efficiency, communication stability, and infrastructure reliability.

XIII. FUTURE SCOPE

While the proposed system effectively addresses beam reliability prediction and railway beam defect detection for high-speed railway environments, several enhancements can be explored to further improve its performance, scalability, and real-world applicability.

One major area for future improvement is the integration of real-time data. By incorporating live data streams from onboard train sensors, High-Altitude Platforms (HAPs), and Internet of Things (IoT) devices, the system can perform real-time beam tracking and infrastructure monitoring. This would enable faster response to dynamic changes in train speed, environmental conditions, and network congestion.

The system can also be enhanced through edge computing deployment. Deploying machine learning and deep learning models on edge devices located on trains or HAPs would reduce latency and dependency on centralized servers. This approach would be particularly beneficial for time-critical communication and safety applications.

Another potential extension involves expanding the defect detection module. Instead of binary classification, future models can be trained to identify specific types of defects such as cracks, corrosion, deformation, or structural fatigue. Severity-level classification can further assist maintenance teams in prioritizing repair activities.

The beam reliability prediction module can be improved by incorporating advanced deep learning models and reinforcement learning techniques that adapt continuously to changing operational conditions. Self-learning models trained on accumulated historical and real-time data would improve prediction accuracy over time.

Additionally, the platform can be extended to support multi-platform accessibility. Developing mobile and tablet-based versions of the application would allow railway staff to access predictions, alerts, and visualizations during field operations.

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