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Combining AI and Machine Learning with Building Data Modeling to Detect and Locate Defects in Railway Infrastructure

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Abstract

Owing to the elevated need for the railway system nowadays, the velocity and capacity of locomotives are inclined to rise. The impact of the harsh climate is concurrently worsening. This leads to degrading railway infrastructures (RI), resulting in flaws. Deficiencies may impact customer satisfaction and the operational security of the RI. Early detection of faults in RI helps mitigate operational risks, save maintenance costs, and enhance resource handling efficiency. This study integrated Artificial Intelligence (AI) and machine learning (ML) with building data modeling (BDM) to identify and pinpoint faults in RI. The BDM model proposed in the research may be completely integrated with ML and AI to identify problems in RI using the established process. The Convolutional Neural Network (CNN) model yields the optimal results. The study's findings indicate that the amalgamation of BDM with ML and AI is feasible and benefits the railway sector.

Keywords: Railway Infrastructures, Artificial Intelligence, Machine Learning, CNN, Building Data Modelling.

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Overview of the Research

The need for RI is rising due to its safe and economical transport methods. The velocity and burden of railway equipment are inclined to rise—furthermore, global warming and environmental degradation result in extreme weather situations. Consequently, RI declines more rapidly, leading to the emergence of problems. Defects may impact passenger comfort, generate noise, or lead to severe occurrences like accidents [1]. Early detection of faults helps mitigate adverse impacts and uphold passenger enjoyment, security, and effective asset administration.

Railway examination may be performed using several methods, including visual rail examination, acoustic assessment, electromagnetic induction detectors, and eddy current testing. The deployment of AI and ML is focused on identifying railway problems due to its autonomous testing capabilities, rapid execution, and reduced inspection costs for RI [2]. Various AI methodologies may be used to create models for defect detection. Effective use of AI in railway problem detection requires enough data and effective information handling. BDM is a methodology for maintaining information across the project lifecycle. The amalgamation of BDM and AI will optimize their advantages. The BDM framework has information about RI elements, which may be employed through the project's entire life cycle [3][8].

This research seeks to amalgamate BDM with AI and ML to identify concurrent problems in RI. Forged joint and agreement serve as instances to study. Data is produced via simulations using a validated program. The BDM model is constructed to include data, and prediction models are developed using CNN.

Related Works

BDM has been utilized for construction projects in RI for an extended period. The advancement of BDM use in construction has progressed to 6D. The use of BDM in the RI is significant, yet its implementation remains relatively limited. Efforts are being made to use BDM in the railway network. Authors in [4] implemented digital twin or BDM technology concerning the long-term reliability of railway turnouts. They illustrated efficient methods for using BDM in railway turnouts throughout several phases of the construction lifecycle.

AI may be used to enhance the velocity characteristic of locomotives. [5] used random forest (RF) classification and support vector machine (SVM) classification to compute speed profiles and utilization of energy. The generated models demonstrated the capability to compute energy use with an error margin of 0.2kWh or fewer and reduced power utilization by 3.01%. AI has been employed to enhance security at railway stops.

Authors in [6] used computer vision to identify curvature. Processing of images has been used in previous research to detect railway problems. The more sophisticated method for identifying rail problems used a 3D laser with a precision of 93%. Scientific research indicates that processing images was a prevalent approach that necessitated the installation of supplementary equipment. The implementation of modern approaches, like laser sensors, was also necessary. Consequently, a different approach that is both cost-effective and dependable, such as AI, is intriguing for use in RI fault detection [7].

The combination of BDM, ML, and AI in the RI has not yet been accomplished. The advancement of prediction algorithms for identifying combination flaws is constrained. This research seeks to address this gap by illustrating the integration of BDM and AI and the ability of AI algorithms to identify cumulative problems in RI.

Methodology

The first phase of this investigation involves the creation of a BDM model. This research utilizes a BDM model to depict the alignment of a dual-track RI construction. The BDM framework is created utilizing AutoCAD 3D and is intended to be a 6D BDM simulation. The models used in this research pertain to the duration, expenses, and service dimensions. The developmental process may be articulated as follows:

The 3D BDM design is constructed according to the horizontal and vertical orientations. This encompasses all essential elements of the railway path, including points of junction, elevated levels, radius of curves, and slope. The design must adhere to the established criteria. The app offers functionalities to identify these connections. The program will provide a notice if the bending angle is insufficient for the desired velocity. In this phase, specimen lines are delineated to signify line segments. In this research, sample lines are established at intervals of 25 m, resulting in each part of the BDM design measuring 25 m in length. Following the vertical and horizontal positioning design, the subsequent and critical phase defines the installation.

This research delineates an outline of the railway track. This stage defines rail elements, including tracks, sleepers, embankments, foundations, retaining walls, and bridges. The subsequent phase involves the building of corridors. This process integrates vertical positioning, horizontal positioning, and installation to form the pathway as a three-dimensional solid. The 3D material gets exported as a Sector Foundation Concepts (SFC) file, ensuring interoperability and compatibility with other BDM tools. The 3D BDM design is generated in this phase. This research illustrates a conventional dual track and railway tunneling, as seen in Figure 1.



(a) (b)

Fig. 1: Instances of 3D BDM Designs: (a) Dual-track; (b) Railway Tunnel

Construction planning software is used to advance the BDM framework to 4D. This research used Navisworks to associate railway elements with the project timeline. Any rail elements may be planned according to the specified degree of detail. The design is integrated into Navisworks using the generated SFC file. The established schedule may be administered with well-recognized software to manage projects, such as MS Project. The project's advancement may be monitored, and its modeling can be conducted. The 4D BDM design is derived from the 3D model. The structure established in the 3D development process is utilized to compute the size and price of the entire endeavor. Rail elements and topography determine the amount. The length of rails is determined by integration, whereas soil work is assessed according to orientation and topography. Civil 3D has a feature to compute this amount. Computation techniques are diverse and may be used according to desire. The scheduling tool included in Civil 3D may do this task. The itinerary in Civil 3D pertains to the columnar functionality rather than scheduling time.

The 6D BDM design is created for servicing objectives. This stage encompasses the operational features outlined in the design. Some included data examples include design velocity, locomotive volume, and accelerator. This data is retained in the framework using Attribute Set Specifications. A novel Attribute Specification may be added individually or electronically; however, the automated method is more efficient and requires assistance from additional software. One-value asset specifications may be included in the system; nevertheless, multiple-value or time-varying Product Specifications are unsuitable for inclusion in the BDM model since they needlessly increase the model's scope and impede workflow efficiency. This research suggests that time-series attribute specifications should be included in the framework as alternative links. The 6D BDM model has been developed and prepared for ML integration.

Embedded sensors or site inspections may gather information. Subsequently, data is converted for appropriate preservation and use. Data collected may be saved on servers, in the cloud, or inside a regional library. This research utilizes a regional archive for demonstration purposes. At this point, the information is prepared for synchronization with the BDM framework. Various neural network architectures—DNN, CNN, and RNN—are employed to create prediction models for fault identification. The rationale for using these approaches includes their appropriateness for irregular problems, their applicability to time-series information, and their demonstrated efficacy in addressing such issues. The challenge for this work's ML and AI models is the regression issue since the predicted values are ongoing.

The primary attribute of the CNN framework is its feature acquisition component. This characteristic distinguishes CNN as it eliminates the need for feature engineering expertise in model development; the computer autonomously does this task. Consequently, if the model is adequately constructed, it selects the optimal collection of characteristics for prediction. The extraction of features component of the CNN model comprises convolutional

levels, while levels for pooling and dropout levels are configurable. Pooling levels are implemented to reduce the dimensions of the visualization of features, hence accelerating learning, while dropout techniques are utilized to mitigate excessive fitting. Another characteristic of the CNN model is its regression or classification component, with this research focusing on the regression aspect. The regression component has the same property as the DNN model since it comprises completely linked or dense layers.

Conclusion

This study combined Artificial Intelligence (AI) and machine learning (ML) with building data modeling (BDM) to detect and locate faults in RI. The BDM model suggested in the study can be fully integrated with ML and AI to detect issues in RI via the defined procedure. The generated BDM model is intended to be the 6D BDM model. The model is created on AutoCAD 3D. The BDM design is created as a 3D Solid to ensure compatibility with other BDM tools and may be downloaded as an SFC file, a typical format for BDM designs. The Convolutional Neural Network (CNN) model produces ideal results, and the study's findings suggest that integrating BDM with machine learning and artificial intelligence is viable and advantageous for the railway industry.

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