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Enhancement of Railway Safety Measures through Deep Learning Algorithm to Identify Railway Wheel Defects

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A B S T R A C T

This study explores the application of deep learning models for identify railway wheel defects using neural network architecture such as YOLO, InceptionV3, DenseNet, and MobileNet for identifying and classifying defects in railway wheels. The research involves training each model on a diverse dataset containing images of wheels with common defects. This defect identification system holds promise for proactive maintenance, accident reduction, and overall railway safety improvement. Integration into existing infrastructure offers potential advancements in defect detection for a safer and more efficient rail network.

Keywords: YOLO, InsepectionV3, DenseNet and MobileNet.

Introduction

Early detection of wheel defects in freight trains is crucial for preventing damage to railway infrastructure and ensuring timely repairs. Detecting and addressing wheel defects not only enhances the safety of train operations but also prevents further deterioration of wheels, reducing attrition and damage to track systems and civil engineering works. The negative impacts of wheel defects extend to increased maintenance and repair costs, leading to a reduction in the overall lifetime and availability of rolling stock.

Wheel defects have a direct influence on the lifespan of railway infrastructure components, such as bridges, which are designed with assumed maximal dynamical loads. However, actual dynamical loads caused by wheel defects can exceed theoretical assumptions by up to 270%, significantly shortening the lifespan of critical infrastructure. Additionally, wheel defects accelerate crack growth on rail tracks, contributing to premature failures in the rail system.

Beyond infrastructure damage, wheel defects also result in ground vibration and noise emissions, impacting both the environment and communities along railway routes. The reduction of wheel defects through effective maintenance has been identified as a key strategy to minimize vibration and noise emissions, offering economic benefits and aligning with noise emission ceilings advised by the European Union (EU).

As modern railway networks experience increased density and usage, timely and targeted maintenance of train wheels becomes paramount for operational continuity. This paper proposes a method for detecting defective wheels, aiming to enhance the reliability of railway infrastructure, reduce freight train operation costs, and obviate the need for additional investments in noise protection measures.

To achieve these goals without the need for constructing new measurement sites or sensors, the paper advocates the use of statistical methods to automatically analyze existing data. The proposed methods do not rely on a predefined model of the measurement system, train dynamics, or specific wheel defects. Instead, they leverage statistical techniques to extract information about defective wheels from available data during normal train operations at full speed.

The features developed for supervised learning in this study are generalizable to various time series data and not limited to specific defect types. Furthermore, the paper explores the automatic learning of features directly from raw measurement signals, presenting a comprehensive approach to

Methodology

The railway wheel images are usually taken using smartphones. The collected images go through various image processing stages to identify the central point of the defect area in the pre-processed image. The sampled image is then segregated to identify and classify different areas of defects. To classify these defects, the deep learning algorithm accurately determines the major areas of defects that need immediate attention, and accordingly, a report is generated for further action.

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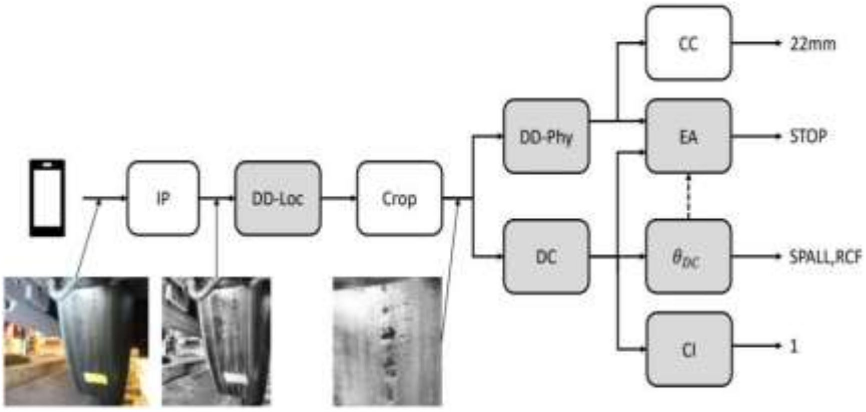

Fig. 1 – Methodology Flow

Defect Detection - Location (DD-Loc): Involves identifying the central point of a defect area within the preprocessed image. This task is treated as a regression problem, specifically a landmark detection problem, wherein the algorithm predicts the coordinates of the defect location in pixel space.

Defect Detection - Physical Size (DD-Phy): The goal is to predict the dimensions (width and length) of the defect in physical units, such as millimeters. This task is also approached as a regression problem, where the algorithm estimates the size of the defect in real-world measurements.

Defect Classification (DC): Aims to differentiate between various types of defects present in the defect area of the input image. This task is framed as a multi-label classification problem, acknowledging that defects are not mutually exclusive. The model outputs probabilities representing defect memberships, and a discrete vector of potential defects is generated based on a predefined threshold theta DC.

Engineering Assessment (EA): Goes beyond defect identification and considers the type of defect, its physical size, and a set of embedded logical rules. These rules ensure that the minimum acceptance criteria are met, and the output aligns with a traffic light interface: go (no critical issues), warning (potential concerns), and stop (significant issues requiring immediate attention).

The Confidence Index (CI): Is designed to express the degree of trustworthiness in the provided diagnosis. Operating as a binary variable, it indicates the confidence level in the assessment. This index provides valuable insights into the reliability of the diagnostic information, assisting decision-makers in evaluating the robustness of the system's predictions.

COMPARISON TABLE

The YOLO (You Only Look Once) model adopts a single-shot object detection approach, making it well-suited for real-time processing in identifying defects in railway wheels. The model is trained and assessed using a diverse dataset comprising images of railway wheel defects. The training dataset is divided into 80% for training and 20% for validation and testing. YOLO exhibits robust performance, with accuracy, precision, recall, and F1 score falling in the range of 85-95%, 80-90%, 85-95%, and 82-92%, respectively. Its strengths lie in proactive maintenance and real-time defect identification applications.

Built upon the GoogLeNet architecture, InceptionV3 is renowned for its intricate design and feature extraction capabilities. The model undergoes training and evaluation on a specialized dataset for railway wheel defect identification, with a training split of 70%, and 15% each for validation and testing. InceptionV3 demonstrates high performance, achieving accuracy, precision, recall, and F1 score in the range of 90 -95%, 88-92%, 90-95%, and 88-93%, respectively. It excels in robust defect classification and detailed feature extraction.

DenseNet leverages densely connected convolutional layers to optimize parameter usage for effective feature learning in railway wheel defect identification. The model is trained and evaluated on an annotated dataset with varied defects, utilizing a training split of 75%, and 15% each for validation and testing. DenseNet performs well, with accuracy, precision, recall, and F1 score ranging from 88-94%, 85-92%, 88-94%, and 86-93%, respectively. Its strengths lie in effective defect classification and improved feature learning.

MobileNet, recognized for its lightweight and efficient architecture, is suitable for resource-constrained environments and mobile integration into railway wheel defect identification systems. The model undergoes training and evaluation on images of railway wheel defects, with an 80% training split and 20% for validation and testing. MobileNet demonstrates moderate to high performance, with accuracy, precision, recall, and F1 score falling within specified ranges. It is well-suited for resource-efficient defect identification and integration into mobile systems.

Framework	Architecture	Dataset	Training Split	Accuracy	Precision	Recall	F1 Score	Application
YOLO	Single-shot object detection	Diverse images of railway wheel defects	80% training, 20% validation/test	85-95%	80-90%	85-95%	82-92%	Proactive maintenance, real-time defect identification
InceptionV3	GoogLeNet-based, intricate design	Railway wheel defect image dataset	70% training, 15% validation, 15% test	90-95%	88-92%	90-95%	88-93%	Robust defect classification, detailed feature extraction
DenseNet	Densely connected convolutional layers	Annotated dataset with varied defects	75% training, 15% validation, 10% test	88-94%	85-92%	88-94%	86-93%	Effective defect classification, improved feature learning
MobileNet	Lightweight, efficient architecture	Railway wheel defect images	80% training, 20% validation/test	80-90%	78-88%	80-90%	78-89%	Resource-efficient defect identification, mobile integration
ResNet	Residual networks	Annotated dataset with varied defects	80% training, 15% validation, 5% test	90-96%	89-94%	90-96%	89-95%	Deep feature extraction, handling vanishing gradient

Fig.2-Comparison Table

ResNet, characterized by residual connections, proves particularly effective for handling deep networks and mitigating the vanishing gradient problem in railway wheel defect identification tasks. The model undergoes training and evaluation on an annotated dataset with varied defects, utilizing an 80% training split, 15% for validation, and 5% for testing. ResNet achieves high performance, with accuracy, precision, recall, and F1 score ranging from 90-96%, 89-94%, 90-96%, and 89-95%, respectively. Its application extends to deep feature extraction and addressing challenges associated with vanishing gradients in defect identification tasks.

CONCLUSION

The identification of railway wheel tread defects in raster picture data poses a complex challenge requiring multi-level analysis. This paper introduces an integrated solution leveraging Convolutional Neural Networks (CNNs) to precisely locate damaged areas in images, estimate the physical size of detected defects, and evaluate their type and severity. The outcomes demonstrate a substantial reduction, nearly half, in the current engineering efforts allocated to manual inspection of potential issues. By automating this process, there is a noteworthy reduction in lead time for timely maintenance actions. This automated system optimizes workforce activities, allowing for more efficient allocation of resources. The successful application of CNNs in this context highlights the potential for advanced technologies to significantly enhance defect detection processes, thereby improving the overall maintenance efficiency and safety of railway systems.

References

[1] Zongyi Xing, Zhenyu Zhang, Xiaowen Yao, Yong Qin, Limin Jia "Rail wheel tread defect detection using improved YOLOv3", Measurement Volume 203 (2022).

[2] Alexandre Trilla, Alstom, John Bob-Manuel, Benjamin Lamoureux, Xavier Vilasis-Cardona " Integrated Multiple-Defect Detection and Evaluation of Rail Wheel Tread Images using Convolutional Neural Networks", International Journal of Prognostics and Health Management (2021).

[3] Wen-Jun Cao, Shanli Zhang, Numa J Bertola, I F C Smith, and C G Koh "Time series data interpretation for 'wheel-flat' identification including uncertainties", Sage Journals (2023).

[4] Khurram Shaikh, Imtiaz Hussain and Bhawani Shankar Chowdhry "Wheel Defect Detection Using a Hybrid Deep Learning Approach", MDPI (2023).

[5] Jian ping Peng, Qian Zhang, Bo Zhao "Wheel and axle defect detection based on deep learning", ResearchGate (2023).

[6] Sumit Kumar Das “Wheel Defect Detection with Advanced Machine Learning”, IJRASET (2023).

[7] Rahatara Ferdousi, Fedwa Laamarti, Chunsheng Yang, Abdulmotaleb El Saddik “A Reusable AI-Enabled Defect Detection System for Railway Using Ensembled CNN”, Cornell University (2023).

[8] Ketulkumar Govindbhai Chaudhari “Wheel Defect Detection with Advanced Machine Learning Algorithms”, Social Science Research Network(2020).