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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 project introduces a mobile application integrating Convolutional Neural Networks (CNNs) for detecting and classifying defects in railway wheels. Users can capture images of wheels via the device's camera, which are then analyzed using a pre-trained CNN model. The application generates intuitive graphical representations of detected defects in bar graphs to aid maintenance personnel in understanding wheel conditions. Experimental evaluation validates the approach's effectiveness, utilizing metrics like accuracy, precision, recall, and F1 score for reliability assessment.

Keywords: Convolution Neural Networks, mobile application, graphical representation.

1. 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 rai lway 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 wheel defect detection that aligns with the evolving needs of efficient and sustainable railway operations.

2. 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.

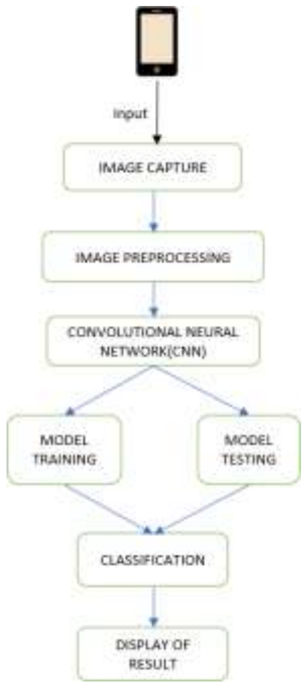

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Fig. 1 – Methodology Flow

1. Image Capture:

The application enables users to capture images of railway wheels using their mobile device's camera. Upon activation of the camera feature within the app, users can take photos of the wheels. These images are then saved or forwarded to the next step for preprocessing.

2. Image Preprocessing:

Preprocessing the captured images is essential to enhance their quality and extract relevant features for defect detection. This step involves several techniques such as resizing the images to a consistent size, normalizing pixel values to a standard range, and reducing noise. Additional methods like edge detection and histogram equalization may also be employed to improve image clarity and facilitate better feature extraction.

3. Convolutional Neural Network (CNN):

The preprocessed images are then input into a Convolutional Neural Network (CNN) model, which can be either pre-trained or custom-built. The CNN comprises layers of convolutional, pooling, and fully connected layers, which work together to extract hierarchical features from the images. Through training, the model learns to recognize patterns associated with various types of defects.

4. Model Training:

Training the CNN model involves optimizing its parameters using a labeled dataset that includes images of both normal wheels and those with defects. During training, the model's weights and biases are adjusted to minimize the difference between the predicted and actual labels of defects. Techniques such as backpropagation and gradient descent are employed to iteratively update the model's parameters, enhancing its performance.

5. Model Testing:

Post-training, the model is evaluated using a separate test dataset to assess its performance and generalization capabilities. Metrics such as accuracy, precision, recall, and F1 score are calculated to quantify the model's effectiveness in correctly identifying defects. This evaluation determines the model's readiness for deployment in real-world scenarios.

6. Classification:

With the model trained and tested, it is ready to classify defects in new, unseen images of railway wheels. The CNN model processes the preprocessed images, predicting the presence and type of defects based on the patterns and features it has learned. The classification results include detailed information about the detected defects, such as their types and severity.

7. Display of Results:

The classification results are displayed to the user through the mobile application interface. This interface may also include graphical representations such as bar graphs generated during the analysis. Users can view the detected defects and their distributions, which aids in understanding the condition of the railway wheels and prioritizing maintenance activities.

3. LITERATURE SURVEY

The presented papers encompass a diverse range of Enhancement of Railway Safety Measures through Deep Learning Algorithm to Identify Railway Wheel Defects. In

[1] This paper delves into the use of Convolutional Neural Networks (CNNs) for detecting and evaluating multiple defects in rail wheel tread images. The CNN model is trained to identify defects such as cracks, spalling, and wear. Leveraging the powerful image recognition capabilities of CNNs, this method aims to enhance the accuracy and efficiency of defect detection.

[2] Presents a hybrid deep learning approach that combines CNNs with other techniques such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks. This hybrid model is designed to capture both spatial and temporal features of wheel defects, thereby improving the detection process. The paper details the architecture, training process, and performance of the hybrid model in comparison to traditional methods.

[3] Explores the use of various conventional machine learning algorithms for detecting rail wheel tread defects. Methods such as Support Vector Machines (SVM), Decision Trees, and Random Forests are applied to classify and identify defects. The focus is on extracting features from wheel tread images and evaluating the effectiveness of these algorithms in terms of accuracy, precision, and computational efficiency.

[4] Introduces a method for detecting train wheel tread defects through image registration techniques. Image registration involves aligning multiple images taken at different times or from different viewpoints. This method compares images of wheel treads over time to detect changes indicative of defects. The paper details the image registration process, the algorithms used for alignment and comparison, and the method's effectiveness in identifying various wheel tread defects.

SI NO	TITLE	AUTHORS	TECHNOLOGIES APPLIED	EXPECTED OUTPUT
01	Integrated Multiple-Defect Detection and Evaluation of Rail Wheel Tread Images using Convolutional Neural Networks	Alexandre Trilla, Alstom, John Bob-Manuel, Benjamin Lamoureux, Xavier Vilasis-Cardona	• Convolutional Neural Networks • PostgreSQL • Apache NiFi • OpenFaaS • REST API	87%
02	Wheel Defect Detection Using a Hybrid Deep Learning Approach	Khurram Shaikh, Imtiaz Hussain and Bhawani Shankar Chowdhry	• multi-layer perceptron (MLP) • deep learning	98%
03	Wheel Defect Detection With Machine Learning	Gabriel Krummenacher, Cheng Soon Ong, Stefan Koller, Seijin Kobayashi, and Joachim M. Buhmann	• Machine learning • support vector machines • supervised learning • artificial neural networks	89%
04	Train Wheel Tread Defects Detection Based on Image Registration	Shoulu Lv, Fuqiang Zhou, Zhenzhong Wei	• Image registration • Ellipse detection Image • segmentation	90%

Fig 1 - Literature Survey

4. SYSTEM ARCHITECTURE

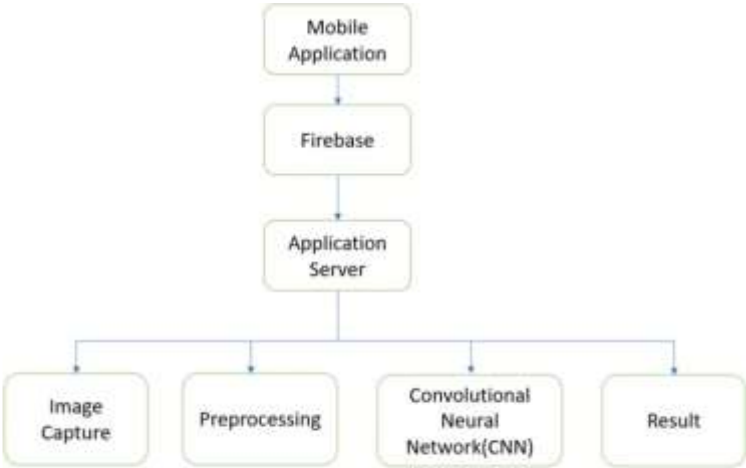

Fig 2- System Architecture

The mobile application serves as the primary interface through which users interact with the system. It facilitates image capture using the device's camera and displays the results of defect detection to the user. The application also handles user authentication and authorization, ensuring secure access to the system's features and data.

Firebase is integrated into the system architecture to provide backend services such as data storage, user authentication, and authorization. It serves as a scalable and reliable platform for storing image data, user information, and other application-related data. Firebase Authentication ensures secure user sign-in, while Firestore offers a NoSQL database for storing and retrieving data in real-time.

The application server, while optional, can be utilized for backend processing tasks such as model inference, defect classification, and integration with external services. It may handle heavy computational tasks or manage large datasets, enhancing the scalability and flexibility of the system. The server communicates with Firebase services and other components to orchestrate data processing and application logic.

5. USE CASE DIAGRAM

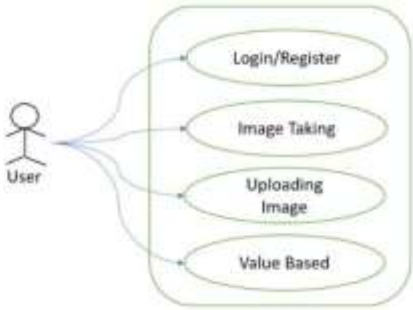

Fig 3- Use Case Diagram

Users interact with the system to either log in or register for a new account. Logging in grants access to the system's features, while registration allows new users to create an account for future access. User has access to the system. User gains access to system functionalities after successful login or registration. Users utilize the system to capture images of railway wheels using their device's camera. This use case allows users to initi ate the image capture process within the application. User is logged in and has access to the image capture feature Captured images are ready for preprocessing and defect detection analysis.

Upload captured images of railway wheels to the system for defect detection analysis. This use case involves transferring the captured images from the user's device to the system's backend for further processing. User has successfully captured images and is logged in to the system.

Users request defect detection analysis based on specific value-based parameters such as weight, passenger number, or shipment details associated with the railway wheels. The system performs defect detection analysis considering these value-based parameters. The system performs defect detection analysis based on the specified value-based parameters and provides classification results indicating the presence and type of defects detected.

6. SEQUENCE DIAGRAM

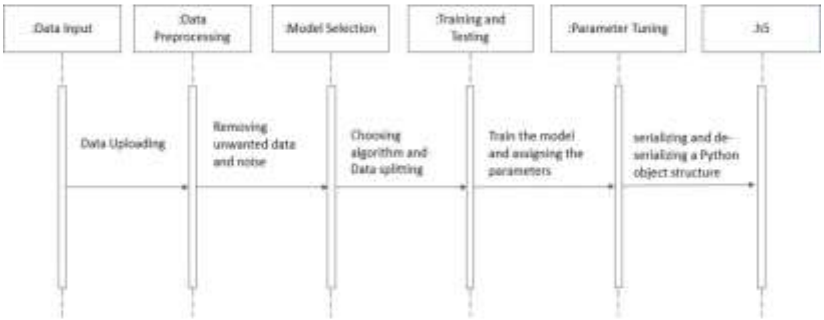

Fig 4- Sequence Diagram

The sequence begins with the Data Input phase, where data, such as images of railway wheels, is provided to the system for defect detection analysis. This interaction involves the user or external sources uploading images to the system.

After receiving the input data, the system initiates the Data Preprocessing phase. Data preprocessing involves various techniques to enhance the quality of the input data and prepare it for defect detection analysis. This may include resizing, normalization, and noise reduction of the input images.

Once the data is preprocessed, the system selects an appropriate model for defect detection. Model selection involves choosing a suitable machine learning or deep learning model, such as a Convolutional Neural Network (CNN), based on factors like dataset size, complexity, and computational resources.

With the selected model, the system proceeds to the Training and Testing phase. During training, the model learns from the preprocessed data to identify patterns associated with different types of defects. After training, the model is tested using a separate dataset to evaluate its performance and generalization capabilities Parameter tuning involves adjusting hyperparameters, such as learning rate, batch size, and network architecture configurations, to enhance the model's accuracy and robustness.

7. IMPLEMENTATION

1. **Mobile Application Development:**

Developing a mobile application with features for capturing images of railway wheels using the device's camera. Implement user authentication and authorization functionalities to ensure secure access to the application. For build mobile application we use java programing language and tools such as android studio, web to application converter.

2. **Image Preprocessing:**

Preprocess the captured images to enhance their quality and prepare them for defect detection. Apply techniques such as resizing, normalization, and noise reduction to standardize the input images.

3. **Convolutional Neural Network (CNN):**

Design and implement a CNN model for defect detection using a deep learning framework such as TensorFlow. Configure the CNN architecture with appropriate layers, including convolutional, pooling, and fully connected layers.

4. **Training and Testing of Model:**

Train the CNN model using a labeled dataset of images containing examples of normal wheels and various types of defects. Split the dataset into training and testing subsets for model evaluation. Utilize techniques such as backpropagation and gradient descent to optimize the model's parameters during training.

5. **Parameter Tuning:**

Conduct parameter tuning to optimize the performance of the CNN model. Adjust hyperparameters such as learning rate, batch size, and network architecture configurations. Explore hyperparameter space using techniques like grid search or random search to identify optimal configurations.

6. **Save Model (.h5):**

Once the CNN model is trained and tuned, save the model's weights and architecture in the Hierarchical Data Format (HDF5) file format (.h5). The saved model can be later loaded and utilized for defect detection analysis in the mobile application.

7. **Integration and Deployment:**

Integrate the trained CNN model into the mobile application for real-time defect detection. Deploy the complete system, including the mobile application and backend services, to production environments such as app stores or cloud platforms.

8. RESULT

Fig 5- Login Page **Fig 6- Registration Page**

[Fig 5] The Home Page provides users with options to upload images by selecting "Choose file," enabling them to initiate defect detection analysis. A "Reload" button allows users to refresh the page for updated content or reset selections. Additionally, the page features a " Value-based" option for users to input specific parameters, such as weight or passenger number, for tailored defect detection analysis.

[Fig 6] The Register Page enables users to create new accounts for the Railway Wheel Defect Detection System, featuring fields for Username, Email, Phone, and Password entry. Users input their desired username, email address, phone number, and password to complete registration.

Fig 7- Home Page **Fig 8- Files Chooser Page**

[Fig 7] The Home Page provides users with options to upload images by selecting "Choose file," enabling them to initiate defect detection analysis. A "Reload" button allows users to refresh the page for updated content or reset selections. Additionally, the page features a " Value-based" option for users to input specific parameters, such as weight or passenger number, for tailored defect detection analysis.

[Fig 8] The Files Choose Page presents users with two options: "Camera" and "Files," allowing them to select the source of the image for defect detection. Upon clicking "Choose file," users can browse their device's files to select an image. Alternatively, users can opt to capture a new image using their device's camera. This interface provides flexibility in image selection, catering to user preferences and convenience.

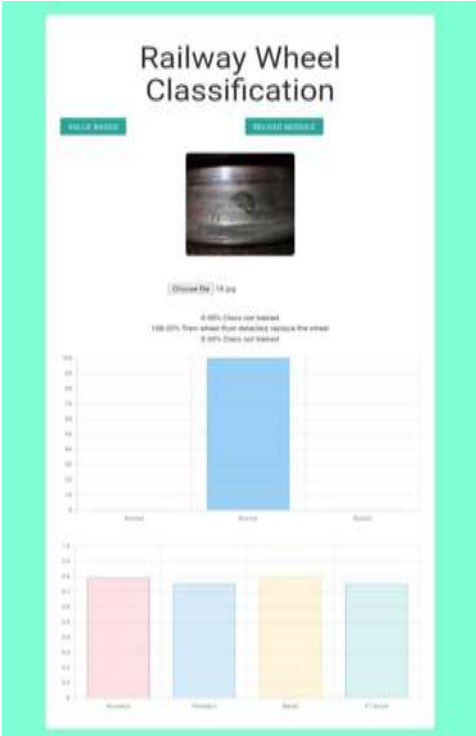

Fig 9- Railway Wheel Image Classification Output Page

[Fig 9] The Railway Wheel Image Classification Output Page displays the uploaded image, allowing users to visually inspect the analyzed result. A bar graph illustrates the distribution of detected defects, showcasing the occurrences of "Dented," "Normal," and "Rust" conditions. Additionally, precision metrics such as accuracy, precision, recall, and F1 score are presented in bar graphs, providing comprehensive insights into the model's performance. Users can interpret the visualizations to understand the classification results effectively. This page enhances user understanding of the defect detection analysis and aids in decision-making for maintenance actions. Its intuitive design facilitates seamless navigation and promotes user engagement with the Railway Wheel Defect Detection System.

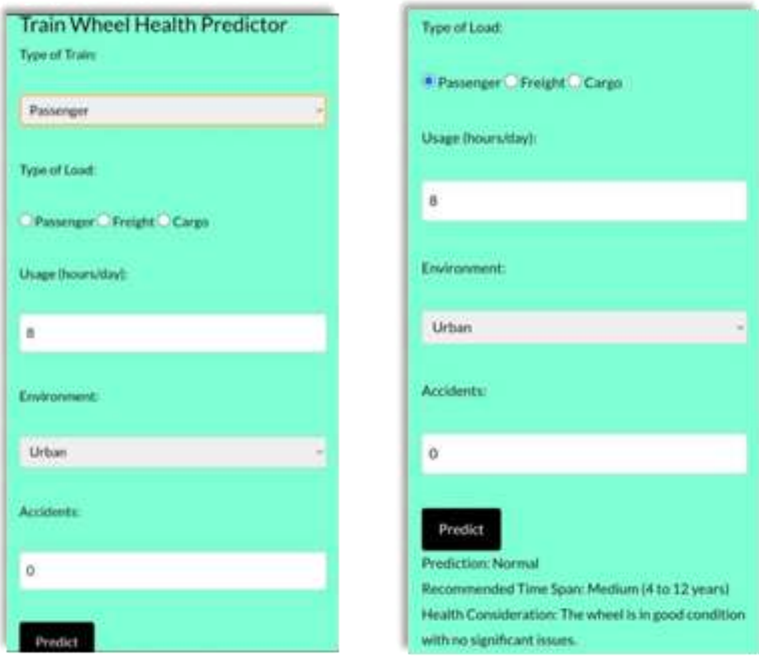

Fig 10- Value Based Output Page

[Fig 10] The Valued-based Output Page presents users with fields to input specific parameters for tailored defect detection analysis. Users can select the "Type of Train" and "Type of Load," specifying relevant details about the railway context. Additionally, options for "Usage" (day/hour) and "Environment" (urban) allow users to provide further contextual information. The page includes a field to indicate any recent "Accidents" related to the railway system. After inputting these parameters, users can initiate the analysis by clicking the "Predict" button. This page enables users to customize defect detection based on real-world factors, enhancing the system's accuracy and relevance to their specific needs.

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.

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