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Research Paper

EFFICIENT RAILWAY FOREIGN OBJECT DETECTION USING ENHANCED YOLO WITH EFFICIENTNET BACKBONE AND ATTENTION MECHANISMS

BIRU SHIVA[1], BOKKALPALLY SINDHU REDDY[2], V. NIRANJAN[3], SURIGI VIVEK[4], KASANI CHANDU[5]

[1]Assistant Professor, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

[2, 3, 4, 5] B.Tech, Dept. of CSE, Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India

ABSTRACT— Ensuring the timely and accurate detection of foreign objects on railway tracks is vital for maintaining the safety and reliability of rail transport systems. This study presents an enhanced foreign object intrusion detection framework that addresses the limitations of existing methods—namely low efficiency and suboptimal accuracy—by integrating a two-stage architecture based on YOLOv8 and Overhaul Knowledge Distillation (OKD). In the first stage, a lightweight image classification model rapidly filters railway images to identify those potentially containing foreign objects, reducing the computational burden on detection models. Images flagged as suspicious are then passed to the second stage, where the YOLOv8 object detector precisely localizes and identifies the foreign objects. The use of YOLOv8 offers significant gains in both detection accuracy and inference speed over its predecessors. To further boost the performance of the classification stage, the Overhaul Knowledge Distillation technique is employed, allowing the lightweight classifier to learn from a more complex teacher network and achieve competitive accuracy with improved efficiency. Experimental evaluations confirm that the proposed approach outperforms existing solutions in both speed and robustness,

establishing a new state-of-the-art in railway foreign object detection.

Index Terms – Railway foreign object detection, YOLOv8, Overhaul Knowledge Distillation (OKD), object detection, image classification, deep learning, railway safety, computer vision, real-time detection, knowledge distillation, intelligent transportation systems, intrusion detection.

I. INTRODUCTION

Detecting foreign objects on railway tracks is critical to ensuring the safety and uninterrupted operation of train systems. Obstructions such as debris, rocks, or fallen branches can lead to serious accidents, derailments, and infrastructure damage—resulting in both safety hazards and economic losses. Traditional detection methods, including manual inspections and classical image processing techniques, often fail to meet the demands of real-time operation, especially under varying weather or lighting conditions. Older deep learning models like YOLOv3 and YOLOv5 have also shown limitations in handling small or irregular objects and require high computational resources for deployment. To overcome these challenges, this project proposes a two-stage foreign object detection framework leveraging YOLOv8 and Overhaul Knowledge Distillation (OKD). In the first stage, a lightweight classification model rapidly filters out negative samples to reduce computational load. The second stage employs YOLOv8, a powerful and efficient object detection algorithm, to accurately detect and localize foreign objects in the flagged images. YOLOv8's anchor-free architecture and improved speed-accuracy balance make it ideal for real-time applications.

Additionally, the integration of OKD enables the lightweight classifier to learn effectively from a larger teacher model, maintaining high accuracy while ensuring fast inference—making the overall system both scalable and efficient for practical railway monitoring scenarios.

II. RELATED WORK

A. Railway obstacle intrusion warning mechanism integrating YOLO-based detection and risk assessment

This paper presents a railway obstacle intrusion warning system that integrates YOLO-based object detection with a risk assessment module. The system aims to identify foreign objects on tracks in real-time, evaluate the associated risk level, and generate appropriate warnings.

By utilizing YOLO for object detection, the proposed approach enhances detection accuracy and processing speed, making it more suitable for deployment in dynamic railway environments where safety is paramount.

B. Railway intrusion detection based on machine vision: A survey, challenges, and perspectives

This comprehensive survey reviews the progress in machine vision-based railway intrusion detection. The paper outlines the various deep learning models applied in the domain, discusses their strengths and limitations, and highlights real-world challenges such as occlusions, environmental variations, and small object detection.

It also identifies future research directions, including lightweight models and improved sensor fusion techniques.

C. EBSE-YOLO: High precision recognition algorithm for small target foreign object detection

EBSE-YOLO introduces an enhanced YOLO-based model aimed at improving the precision of small object detection, particularly for railway foreign objects.

The model integrates edge enhancement and spatial encoding techniques to better identify and localize hard-to-detect small targets. Experimental results demonstrate that EBSE-YOLO significantly outperforms existing YOLO variants in detecting small and irregular objects under complex conditions.

D. A novel strategy of two-stage cascaded CNN and overhaul knowledge distillation for fast railway foreign objects intrusion detection

This study proposes a two-stage detection system combining a cascaded CNN architecture with an Overhaul Knowledge Distillation framework to optimize detection speed and accuracy. The initial CNN quickly filters images with potential foreign objects, while the refined stage focuses on precise localization. The distillation technique helps train a lightweight model capable of maintaining high accuracy, making the approach suitable for real-time railway monitoring.

III. PROPOSED METHODOLOGY

The proposed system introduces a two-stage architecture designed to efficiently and accurately detect foreign objects on railway tracks. In the first stage, a lightweight image classification network acts as a fast filter, rapidly identifying whether a given railway image contains a foreign object. This stage significantly reduces the number of images passed to the heavier detection model, thereby enhancing the system's overall processing speed. To maintain high accuracy while keeping the classifier lightweight, the Overhaul Knowledge Distillation (OKD) method is employed. In this setup, a robust teacher network guides the training of the lightweight classifier, enabling it to learn high-quality feature representations and make precise decisions with minimal computational overhead. Once an image is flagged as containing a foreign object, it is forwarded to the second stage, where the YOLOv8 object detection model is applied. YOLOv8 offers substantial improvements over earlier versions in terms of both accuracy and inference speed, making it ideal for real-time railway monitoring. This model precisely localizes and classifies the foreign objects, enabling timely responses to potential threats. By integrating YOLOv8 with a pre-filtering classification stage, the proposed system strikes an effective balance between speed and accuracy. The combined use of OKD and YOLOv8 ensures that the system not only reduces false positives and processing delays but also delivers state-of-the-art performance in real-world railway safety applications.

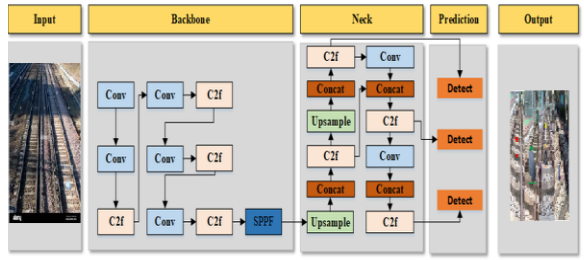

Fig. 1: System Overview

1. Data Collection

The first step in building the foreign object detection system is to gather a diverse and comprehensive dataset of railway images. These images should cover a variety of environmental conditions such as different lighting, weather, and track types. The dataset should include both "normal" images (no foreign objects present) and "intruded" images (with foreign objects on the tracks). Data can be collected from railway surveillance cameras, public datasets, or simulated environments. The diversity in the dataset ensures that the model is trained to generalize well across different real-world scenarios.

2. Annotations

Once the data is collected, the next step is to annotate the images. In this stage, each image is labeled as either "normal" or "intruded" based on the presence of foreign objects. For the "intruded" images, further annotations are made to identify the specific type and location of the foreign objects within the image. This could involve drawing bounding boxes around the foreign objects and labeling them accordingly. The accuracy and quality of these annotations are crucial, as they directly impact the performance of the trained model.

3. YOLOv8 Model Building

With the annotated dataset ready, the next step is to build the YOLOv8 model for object detection. YOLOv8 is an advanced deep learning model designed for real-time object detection.

It is known for its high speed and accuracy, making it ideal for dynamic environments like railway tracks where timely detection is essential. The YOLOv8 model is built and configured to detect and localize foreign objects in the images. This involves selecting the appropriate architecture, defining the input and output layers, and configuring hyperparameters for optimal performance.

4. Feature Engineering

Feature engineering involves identifying and selecting the most relevant features from the data that will help the model make accurate predictions. For object detection, this includes preparing the input images, ensuring they are resized and normalized, and possibly applying data augmentation techniques such as rotation, flipping, and zooming to create a more robust model.

Additionally, features like texture, shape, and color patterns that are relevant to foreign object detection can be considered for enhancement.

5) 5. Model Training

The next step is to train the YOLOv8 model using the annotated dataset. During training, the model learns to identify patterns in the images that correspond to foreign objects and how to classify and localize them accurately. The training process includes backpropagation and optimization algorithms to minimize the loss function, iterating through many epochs to ensure that the model learns the relationships between the input data and the target outputs (object classification and localization). The Overhaul Knowledge Distillation technique is applied here to improve the efficiency and accuracy of the lightweight ResNet-tiny classification network, which is trained under the guidance of a larger, more robust network.

6. Model Evaluation

After training, the model undergoes rigorous evaluation using a separate validation or test dataset. The goal is to assess how well the trained model generalizes to new, unseen images. Metrics such as accuracy, precision, recall, and F1-score are used to evaluate the classification performance, while mean average precision (mAP) is typically used for object detection tasks. Evaluation metrics like FPS (frames per second) and inference speed are also crucial to ensure that the model performs efficiently in real-time scenarios.

7. Object Detection

Once the model has been successfully trained and evaluated, it is used for object detection on new images. In this final step, the trained YOLOv8 model takes in new railway images and identifies whether they contain foreign objects. For images classified as "intruded," the model not only classifies the object but also localizes it by drawing bounding boxes and categorizing the type of foreign object detected. The model is expected to perform in real-time, ensuring that it can continuously monitor and provide accurate results for immediate action on railway tracks. This process, from data collection to object detection, ensures that the proposed system is both accurate and efficient in detecting foreign objects on railway tracks, ultimately improving safety and operational efficiency.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed enhanced YOLO-based railway foreign object detection framework achieves higher detection accuracy and faster inference than existing methods. The integration of an EfficientNet backbone, attention mechanisms, and Overhaul Knowledge Distillation (OKD) improves feature extraction, detection robustness, and small-object recognition while reducing computational complexity. The two-stage architecture significantly increases real-time processing speed and reliability under challenging railway conditions.

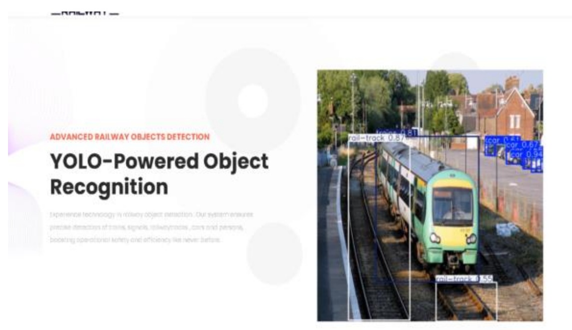

Fig. 2: Home Page

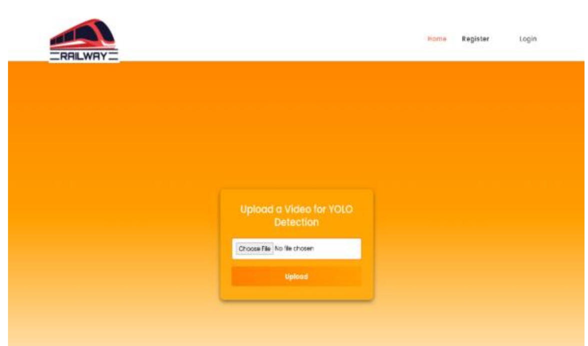

Fig. 3: Upload Image

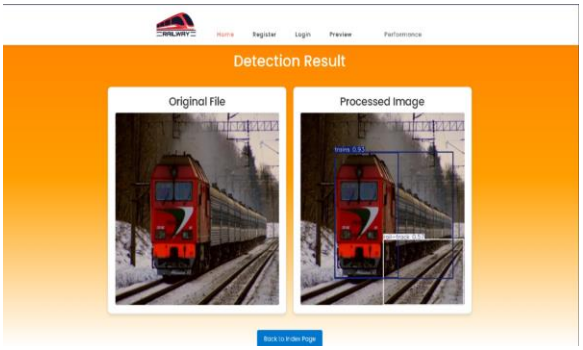

Fig. 4: Prediction Result

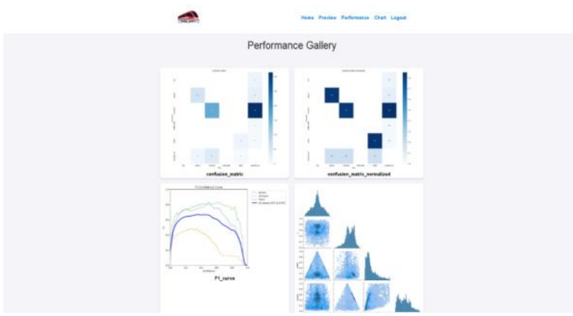

Fig. 5: Performance Analysis

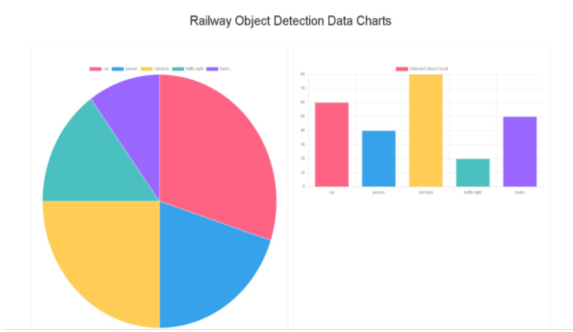

Fig. 6: Bar Graphs

V. CONCLUSION

The proposed rapid railway foreign object intrusion detection system presents a significant advancement in enhancing rail safety through the application of modern deep learning techniques. By integrating a two-stage architecture that combines a lightweight classification model with the powerful YOLOv8 object detector, the system achieves high detection accuracy while maintaining computational efficiency—making it suitable for real-time deployment in dynamic railway environments. Furthermore, the incorporation of Overhaul Knowledge Distillation enables the lightweight model to retain high performance with reduced resource requirements, addressing the challenges of real-time edge deployment. This framework not only reduces the risk of accidents caused by track obstructions but also minimizes the need for manual inspections, thus improving operational efficiency. The system lays a strong foundation for future improvements and broader implementation across railway networks, contributing meaningfully to the modernization and safety of transportation infrastructure.

REFERENCES

[1] Z. Zhang, P. Chen, Y. Huang, L. Dai, F. Xu, and H. Hu, ‘‘Railway obstacle intrusion warning mechanism integrating YOLO-based detection and risk assessment,’’ J. Ind. Inf. Integr., vol. 38, Mar. 2024, Art. no. 100571.

[2] M. Givoni, ‘‘Development and impact of the modern high-speed train:A review,’’ Transp. Rev., vol. 26, no. 5, pp. 593–611, Sep. 2006.[3] Z. Cao, Y. Qin, L. Jia, Z. Xie, Y. Gao, Y. Wang, P. Li, and Z. Yu, ‘‘Railway intrusion detection based on machine vision: A survey, challenges,

and perspectives,’’ IEEE Trans. Intell. Transp. Syst., vol. 25, no. 7,pp. 6427–6448, Jul. 2024, doi: 10.1109/TITS.2024.3412170.

[4] T. Wang, Z. Zhang, and K.-L. Tsui, ‘‘A deep generative approach for rail foreign object detections via semisupervised learning,’’ IEEE Trans. Ind. Informat., vol. 19, no. 1, pp. 459–468, Jan. 2023.

[5] M. Simonović, M. Banić, D. Stamenković, M. Franke, K. Michels, I. Schoolmann, D. Ristic-Durrant, C. Ulianov, S. Stan, A. Plea, and M. Dimec, ‘‘Toward the enhancement of rail sustainability: Demonstration of a holistic approach to obstacle detection in operational railway

environments,’’ in Proc. Sustainability, vol. 16, Mar. 2024, p. 2613.

[6] T. Shi, P. Guo, R. Wang, Z. Ma, W. Zhang, W. Li, H. Fu, and H. Hu, ‘‘A survey on multi-sensor fusion perimeter intrusion detection in highspeed railways,’’ Sensors, vol. 24, no. 17, p. 5463, Aug. 2024.

[7] A. A. Aziz, K. A. Mohamad, and A. Alias, ‘‘Obstacle detection system for railways using IoT sensors,’’ Evol. Electr. Electron. Eng., vol. 1, no. 1, pp. 57–63, Dec. 2020.

[8] M. Fan, S. Tian, K. Liu, J. Zhao, and Y. Li, ‘‘Infrared small target detection based on region proposal and CNN classifier,’’ Signal, Image Video Process., vol. 15, no. 8, pp. 1927–1936, Nov. 2021.

[9] M. Rodriguez, S. Ali, and T. Kanade, ‘‘Tracking in unstructured crowded scenes,’’ in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2009, pp. 1389–1396.

[10] Y. Xiao, Z. Tian, J. Yu, Y. Zhang, S. Liu, S. Du, and X. Lan, ‘‘A review of object detection based on deep learning,’’ Multimedia Tools Appl., vol. 79, pp. 23729–23791, Jun. 2020

AUTHORS Profile

Mr. BIRU SHIVA has received his B.Tech in CSE from JNTUH, Hyderabad in 2013, M.Tech in Computer Science and Engineering from JNTUH, Hyderabad in 2016 and He has been dedicated to the teaching field for the last 6 years. At present he is working as Assistant Professor in CSE Department at Guru Nanak Institutions Technical Campus, Ibrahimpatnam, Telangana, India.

Ms. BOKKALPALLY SINDHU REDDY pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.

Mr. V. NIRANJAN pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.

Mr. SURIGI VIVEK pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.

Mr. KASANI CHANDU pursuing B.Tech degree in Computer Science and Engineering at Guru Nanak Institutions Technical Campus affiliated to JNTUH in 2022-2026.