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Efficient Railway Foreign Object Detection Using Enhanced YOLO with Efficient Net Backbone and Attention Mechanisms

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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.
Keywords:YOLOv8,YOLOv5, Deep Learning, Computer Vision, Overhaul Knowledge Distillation (OKD), Convolutional Neural Network (CNN), Attention Mechanisms (CBAM).

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.LITERATURE SURVEY

Z.Zhang, P.Chen, Y.Huang, L.Dai, F.Xu, and H.Hu (2024) 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[1], the proposed approach enhances detection accuracy and processing speed, making it more suitable for deployment in dynamic railway environments where safety is paramount.

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Z.Cao,Y.Qin,L.Jia,Z.Xie,Y.Gao,Y.Wang,P.Li,and Z.Yu(2024) 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[2]. It also identifies future research directions, including lightweight models and improved sensor fusion techniques.

S.Meng,W.Chen, and Y.Jiang (2024) 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[3]. 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.

S.Wang,Y.Wang,Y.Chang,R.Zhao,and Y.She(2023)EBSE-YOLO introduces an enhanced YOLO-based model aimed at improving the precision of small object detection, particularly for railway foreign objects[4]. 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.

III. EXISTING SYSTEM

The existing system for railway foreign object detection mainly relies on manual inspections and sensor-based methods such as infrared and ultrasonic sensors, which are costly, labor-intensive, and less reliable under varying environmental conditions like poor lighting and bad weather. Early computer vision techniques, including edge detection and motion tracking, faced issues such as false detections and inability to handle dynamic or complex scenes[5,6,7]. Although deep learning models like YOLOv3, YOLOv4, and YOLOv5 improved detection speed and accuracy, they still struggle with detecting small or partially hidden objects and require high computational resources. Additionally, limitations such as dependence on anchor boxes and reduced performance on edge devices make existing systems less efficient for real-time railway safety applications.

Existing System Disadvantages

- False Positives and Missed Detections
- Dependence on High-Quality Training Data
- Limited Performance in Harsh Weather

Proposed System

The proposed system introduces a two-stage architecture for efficient and accurate railway foreign object detection. In the first stage, a lightweight image classification model acts as a fast filter to identify images that may contain foreign objects, reducing the computational load on the system. This stage uses Overhaul Knowledge Distillation (OKD) to improve accuracy while maintaining a lightweight design. In the second stage, the YOLOv8 model is applied to precisely detect and classify objects in the filtered images. This combination enhances both speed and accuracy, reduces false detections, and enables real-time monitoring, making the system highly effective for railway safety applications[8,9,10].

Proposed System Advantages:

- High Accuracy
- Real-Time Performance
- Lightweight and Deployable
- Efficient Two-Stage System

IV. SYSTEM ARCHITECTURE

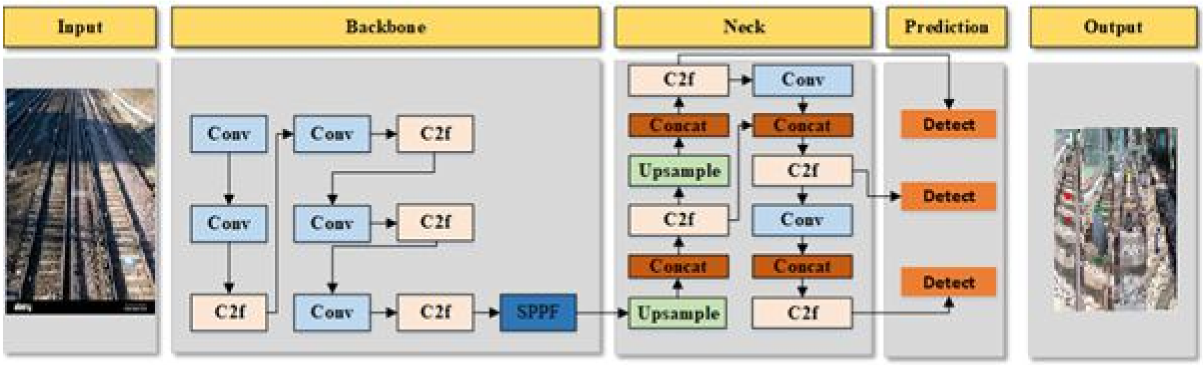

Figure 1: System Architecture

The system architecture is based on the YOLOv8 object detection framework, which consists of five main components: input, backbone, neck, prediction, and output[11]. The input stage receives railway track images, which are then processed by the backbone network using convolution (Conv) and C2f modules to extract important features, along with an SPPF layer to capture multi-scale information[12]. These features are passed to the neck, where operations like up sampling and concatenation (Concat) are performed to combine low-level and high-level features, improving detection of small and complex objects. In the prediction stage, the model uses multiple detection heads to identify objects at different scales. Finally, the output stage provides the detected foreign objects with bounding boxes and class labels, enabling accurate and real-time railway track monitoring.

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Methodology

Modules Name:

- Data Collection
- Annotations
- Yolov8 Model Building
- Feature Engineering
- Model Training
- Model Evaluation
- Object Detection

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[13]. 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 labelled 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[14,15].

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) 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.

V. IMPLEMENTATION

This project is designed as an intelligent system to detect foreign objects on railway tracks using a two-stage deep learning approach. When the system runs, it first collects and processes railway images or video frames from surveillance sources. The input data is then pre-processed by resizing, normalizing, and enhancing image quality to improve detection performance. In the first stage, a lightweight image classification model is used to quickly filter images and identify those that may contain foreign objects, reducing unnecessary computation. This classifier is trained using Overhaul Knowledge Distillation (OKD), which helps it learn efficiently from a larger model while remaining lightweight. The filtered images are then passed to the second stage, where the YOLOv8 model is used for detailed object detection. The model extracts features using convolutional layers and processes them through backbone and neck networks to detect objects at multiple scales. It then predicts bounding boxes and class labels for detected objects such as stones, debris, or obstacles on railway tracks. The system analyses the image context to accurately identify even small or partially hidden objects.

Finally, the detected results are displayed with bounding boxes and labels, and alerts can be generated for safety monitoring. This implementation ensures real-time detection, high accuracy, and efficient performance, making it suitable for practical railway surveillance applications.

Algorithm Used

Existing Algorithm

The existing technique uses YOLOv5s, a lightweight and efficient single-stage object detection model designed for real-time applications. It divides the input image into grids and predicts bounding boxes and class probabilities simultaneously, ensuring fast detection. To enhance feature extraction, EfficientNet is used as the backbone for better performance with fewer computations, while the Convolutional Block Attention Module (CBAM) improves focus on important spatial and channel features, especially for small objects. Additionally, the K-means++ algorithm is applied to optimize anchor box sizes, which improves detection accuracy and training stability.

Proposed Algorithm

The proposed technique uses YOLOv8 for accurate and real-time detection of foreign objects on railway tracks. Unlike earlier versions, YOLOv8 follows an anchor-free approach, which improves detection of small and irregular objects. It features an enhanced backbone and head structure for better feature learning, resulting in higher accuracy and faster processing compared to YOLOv5. In this system, YOLOv8 is applied as the second stage after a lightweight classifier filters the input images, reducing computational load while maintaining high performance. This two-stage approach ensures efficient, reliable, and real-time railway monitoring.

VI. EXPERIMENTAL RESULTS

REGISTRATION / LOGIN PAGE:

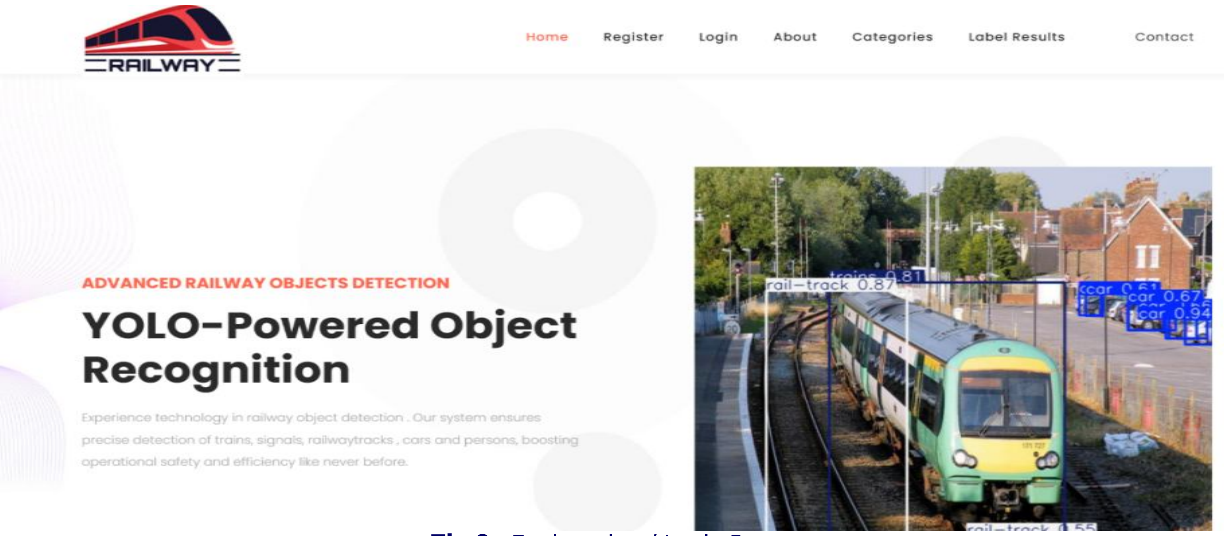

Fig 2 : Registration / Login Page

The Registration / Login page of the Railway Foreign Object Detection System provides a simple and user-friendly interface that introduces YOLO-based object detection technology. It includes a navigation bar for easy access to features like registration, login, and results. The page also displays a sample image with detected objects such as trains and tracks, highlighting the system's ability to perform accurate and real-time detection to improve railway safety.

REGISTRATION PAGE :

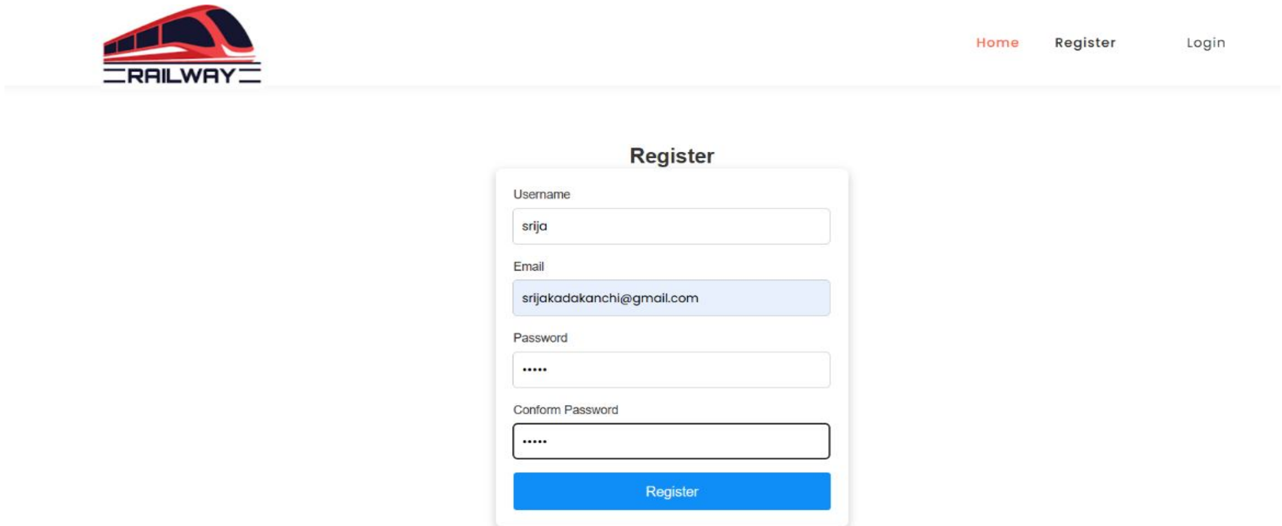

Figure 3 : Registration Page

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The registration page allows new users to create an account by entering details such as username, email, and password. It includes a confirmation field to ensure password accuracy and provides a simple and secure interface for user sign-up. This page enables users to access the system's features like object detection and result viewing after successful registration.

LOGIN PAGE :

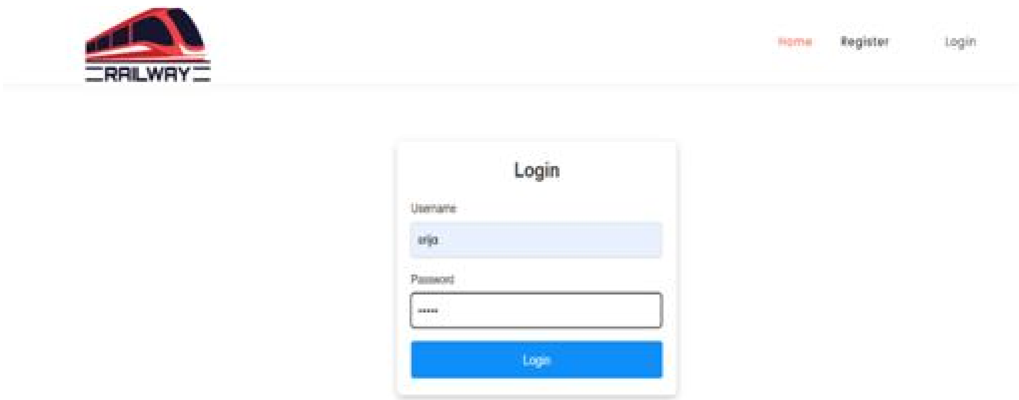

Fig 4 : Login Page

The login page allows registered users to securely access the system by entering their username and password. It provides a simple and user-friendly interface for authentication, ensuring that only authorized users can use features like object detection and result viewing.

UPLOAD PAGE :

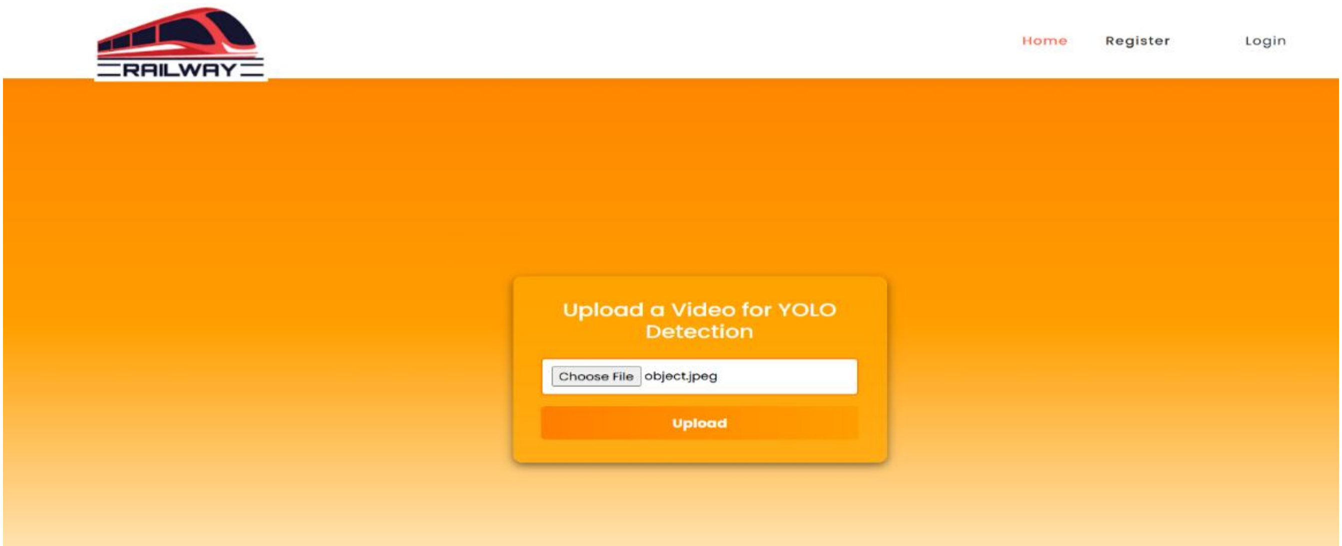

Figure 5: Upload Page

This page allows users to upload images or videos for object detection using the YOLO model. It provides a simple interface to select files and initiate the detection process, enabling users to analyze railway scenes and identify objects efficiently.

DETECTION PAGE:

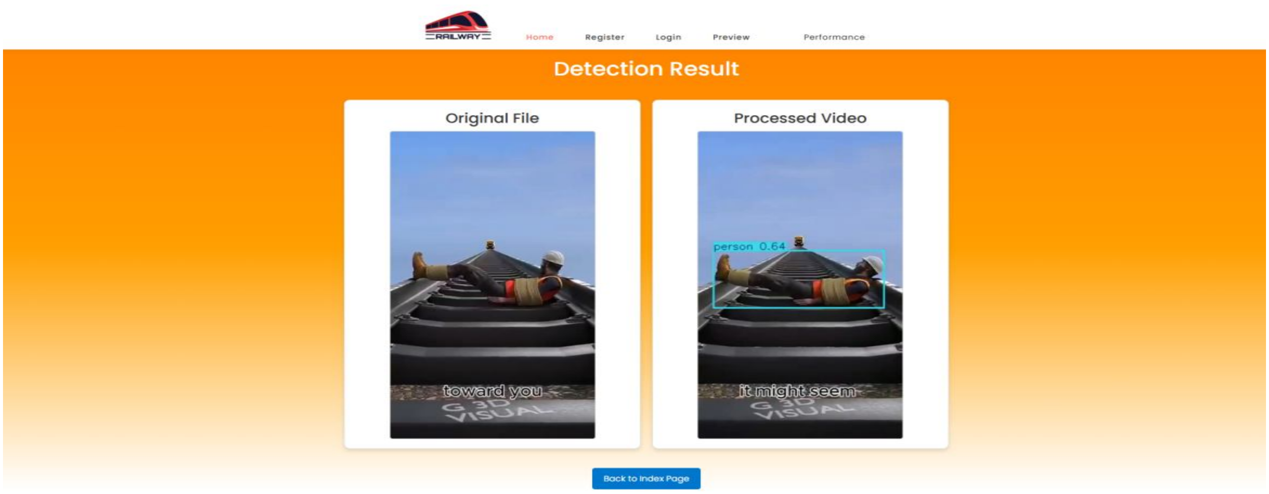

Figure 6: Detection Page

This page displays the results of the object detection process by showing both the original image and the processed image with detected objects highlighted using bounding boxes and confidence scores. It helps users easily compare and understand the detection output generated by the YOLO model.

Performance Page:

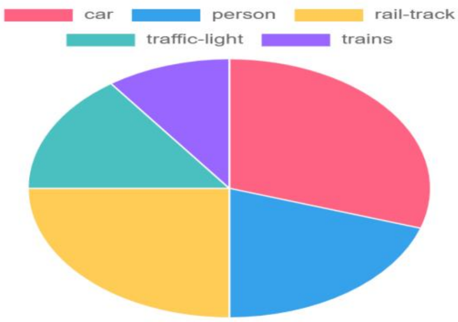

Figure 7 : Performance Page

The above images represent sample outputs and dataset insights of the object detection system developed using the YOLOv8 model. The first image appears to be a processed or partially visualized frame from the system, which may include input data or intermediate detection output, indicating how the model handles real-world images during processing. The second image shows a class-wise distribution graph, where different object categories such as car, person, rail-track, traffic light, and trains are represented. This graph helps in understanding how the dataset is distributed across various classes, highlighting whether the data is balanced or biased toward certain categories. Such visualizations are important for improving model performance, as they help identify the need for additional data collection or balancing techniques to ensure accurate and reliable object detection.

VII. 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.

VIII. FUTURE ENHANCEMENT

An important future enhancement for the railway foreign object detection system is the integration of self-supervised learning, which allows the model to learn from large amounts of unlabeled real-world data and continuously improve its performance. This helps the system adapt to changing environments, new object types, and varying conditions without requiring manual annotation. Additionally, incorporating a feedback-based active learning approach, where uncertain detections are reviewed by humans, can further improve accuracy by reducing false positives and missed detections. Combined with edge computing for faster on-site processing, these improvements can make the system more adaptive, reliable, and efficient for real-time railway safety monitoring.

REFERENCES

1. Z. Zhang, P. Chen, Y. Huang, L. Dai, F. Xu, and H. Hu, ''Railwayobstacle 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.
3. T.Wang, Z. Zhang, and K.-L. Tsui, ''A deep generative approach for railforeign object detections via semisupervised learning,'' IEEE Trans. Ind.Informat., vol. 19, no. 1, pp. 459–468, Jan. 2023.
4. M.Simonović, M.Banić, D. Stamenković, M. Franke, K. Michels,I. Schoolmann, D. Ristic-Durrant, C. Ulianov, S. Stan, A. Plea, andM. Dimec, ''Toward the enhancement of rail sustainability: Demonstrationof a holistic approach to obstacle detection in operational railway environments,'' in Proc. Sustainability, vol. 16, Mar. 2024, p. 2613.
5. 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.
6. 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.
7. M.Fan, S.Tian, K.Liu, J.Zhao, and Y.Li, ''Infrared small target detection based on region proposal and CNN classifier,'' Signal, ImageVideo Process., vol. 15, no. 8, pp. 1927–1936, Nov. 2021.

8. M.Rodriguez, S.Ali, and T.Kanade, ‘‘Tracking in unstructured crowdedscenes,’’ in Proc. IEEE 12th Int. Conf. Comput. Vis., Sep. 2009,pp. 1389–1396.
9. Z.Silar and M.Dobrovolny, ‘‘Utilization of directional properties ofoptical flow for railway crossing occupancy monitoring,’’ in Proc. Int.Conf. IT Converg. Secur. (ICITCS), Dec. 2013, pp. 1–4.
10. C.Tastimur, M.Karakose, and E. Akin, ‘‘Image processing basedlevel crossing detection and foreign objects recognition approach inrailways,’’ Int. J. Appl. Math., Electron. Comput., vol. 1, pp. 19–23,Aug. 2017.
11. M.Shah, O.Javed, and K.Shafique, ‘‘Automated visual surveillance inrealistic scenarios,’’ IEEE Multimedia Mag., vol. 14, no. 1, pp. 30–39,Jan. 2007.
12. Ali,M.H.,Jaber,M.M.,Alfred Daniel, J. et al. Autonomous vehicles decision-making enhancement using self-determination theory and mixed-precision neural networks. Multimed Tools Appl **84**, 35263–35286 (2025). https://doi.org/10.1007/s11042-023-14375-4
13. Chinnasamy,P.,Dhavamani, L.,Ayyasamy, R.K. et al. QuantumBlock health records: enhancing healthcare data security with quantum cryptography and blockchain technology. Cluster Comput **28**, 474 (2025). https://doi.org/10.1007/s10586-025-05101-w.
14. P.Kadiri, P.Anusha, M.Prabhu, R. Asuncion, V. S. Pavan and J. V. Suman, "Morphed Picture Recognition using Machine Learning Algorithms," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 1-6, https://soi.org/10.1109/ICAIT61638.2024.10690845