EFFICIENT RAILWAY FOREIGN OBJECT DETECTION USING YOLOV8

Kulsum Begum[1], Dr. C. Berin Jones[2]
[1]PG Scholar, Department of CSE, Shadan Women's College of Engineering and Technology, Hyderabad, kulsumm003@gmail.com
[2]Professor, Department of CSE, Shadan Women's College of Engineering and Technology
jonesberin@gmail.com

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ABSTRACT
Maintaining the security and dependability of rail transportation systems depends on the prompt and precise detection of foreign items on railway lines. By combining a two-stage architecture based on YOLOv8 and Overhaul Knowledge Distillation (OKD), this study offers an improved foreign object intrusion detection framework that solves the drawbacks of current approaches, specifically low efficiency and suboptimal accuracy. To lessen the computational load on detection models, a lightweight image classification model quickly filters railway photos to find those that might include foreign items. The YOLOv8 object detector precisely locates and identifies the foreign objects in images that have been marked as suspicious. YOLOv8 provides notable improvements over its predecessors in terms of inference speed and detection accuracy. The Overhaul Knowledge Distillation technique is used to further improve the classification stage's performance, enabling the lightweight classifier to learn from a more intricate teacher network and attain competitive accuracy with increased efficiency. The suggested method establishes a new state-of-the-art in railway foreign item detection by outperforming current solutions in both speed and robustness, according to experimental evaluations.

1. INTRODUCTION

For train systems to operate safely and continuously, it is essential to detect foreign items on railway rails. Debris, boulders, and fallen branches are examples of obstructions that can cause major mishaps, derailments, and infrastructure damage, posing a risk to public safety and causing financial losses. The demands of real-time operation are frequently not addressed by traditional detection methods, such as human inspections and conventional image processing approaches, particularly in situations with changing lighting or weather. Older deep learning models, such as YOLOv3 and YOLOv5, have also demonstrated shortcomings when it comes to handling small or irregular objects, and their implementation requires a lot of processing power. This research suggests a two-stage foreign object detection methodology that makes use of Overhaul Knowledge Distillation (OKD) and YOLOv8 to address these issues. In order to minimise computational effort, a lightweight classification model quickly eliminates negative samples in the first stage. YOLOv8, a potent and effective object detection method, is used in the second stage to precisely identify and locate foreign items in the flagged photos. YOLOv8's enhanced speed-accuracy balance and anchor-free architecture make it perfect for real-time applications. Furthermore, the lightweight classifier may learn efficiently from a bigger teacher model because to the inclusion of OKD, keeping high accuracy while guaranteeing quick inference. This makes the system as a whole both scalable and useful for real-world railway surveillance scenarios.

2. EXISTING SYSTEM OF PROJECT

- Historically, railway foreign object detection has relied on fixed sensor-based systems, including ultrasonic or infrared sensors, and manual inspections. Despite their widespread use, these techniques have a number of serious disadvantages, including high deployment and maintenance costs, a high labour cost, and performance that is significantly impacted by unfavourable weather, lighting, and visibility conditions. Railway safety is seriously threatened by these restrictions, especially in distant or busy locations where constant surveillance is crucial. Classical computer vision techniques based on motion tracking, edge detection, or background subtraction were employed in early automation attempts. These methods, however, had trouble with dynamic situations and were prone to missed or false positive results, particularly when working with irregular or obscured objects.
- Deep learning-based object detection models, especially the YOLO (You Only Look Once) family, have transformed the field in recent years by providing high-speed, real-time detection capabilities. Although models like YOLOv3 and YOLOv4 showed significant improvements in accuracy and generalisation, they were still unable to detect small, low-contrast, or partially veiled foreign objects, which are frequently found in train contexts. With features including

effective model scaling, mosaic data augmentation, and auto-learning bounding box anchoring, YOLOv5 greatly enhanced performance. However, when implemented on edge devices with limited computational capabilities, the typical YOLOv5s variation (the "small" model) still shows limits. Additionally, it has trouble identifying small-scale intrusions that could pose serious risks, including wires, boulders, or garbage. Additionally, convergence speed, detection accuracy, and adaptation to complicated backdrops may be adversely affected by the use of fixed-scale feature extraction and predetermined anchor boxes.

3. RELATED WORK

Railway obstacle incursion warning system that incorporates risk assessment and YOLO-based detection, Z. Zhang, P. Chen, Y. Huang, L. Dai, F. Xu, and H. Hu are the authors.

The railway obstacle intrusion warning system described in this research combines a risk assessment module with YOLO-based object detection. The system seeks to detect foreign items on tracks in real time, assess the degree of risk involved, and produce the necessary alerts. The suggested method improves detection accuracy and processing speed by using YOLO for object detection, which makes it more appropriate for deployment in dynamic railway contexts where safety is crucial.

Machine vision-based railway intrusion detection: An overview, difficulties, and viewpoints, Z. Cao, Y. Qin, L. Jia, Z. Xie, Y. Gao, Y. Wang, P. Li, and Z. Yu are the authors.

This thorough assessment examines the development of machine vision-based railway intrusion detection. The study describes the many deep learning models used in the field, talks about their advantages and disadvantages, and emphasises practical issues such small object recognition, environmental changes, and occlusions. Future research avenues, such as lightweight models and enhanced sensor fusion methods, are also identified.

4. PROPOSED SYSTEM

1.The two-stage architecture of the proposed system is intended to effectively and precisely identify alien items on railway rails. A lightweight image classification network serves as a quick filter in the first step, quickly determining whether a particular railway image contains a foreign object. This step improves the system's overall processing speed by drastically reducing the quantity of photos sent to the heavier detection model. The Overhaul Knowledge Distillation (OKD) approach is used to retain high accuracy while keeping the classifier lightweight. The lightweight classifier in this configuration can learn high-quality feature representations and make accurate decisions with little computing overhead thanks to the guidance of a strong teacher network.

2. An image is sent to the second step, where the YOLOv8 object detection model is used, once it is identified as having a foreign item. YOLOv8 is perfect for real-time railway monitoring since it significantly outperforms previous iterations in terms of accuracy and inference speed. This model accurately locates and categorises the alien items, allowing for prompt reactions to possible dangers. The suggested solution effectively balances speed and accuracy by combining YOLOv8 with a pre-filtering categorisation stage. In addition to lowering false positives and processing delays, the system's combined usage of OKD and YOLOv8 guarantees cutting-edge performance in practical railway safety applications.

5. MODULES

1. Data Collection:

The collection of a varied and extensive dataset of railway photos is the first stage in developing the foreign object detection system. A range of environmental variables, including various lighting, weather, and track kinds, should be captured in these photos. Both "normal" (no foreign objects) and "intruded" (with foreign objects on the tracks) photos should be included in the dataset. Public databases, simulated environments, and train surveillance cameras can all provide data. The dataset's diversity guarantees that the model is trained to perform well in a variety of real-world situations.

2. Annotations:

Annotating the photos comes next after the data is gathered. Depending on whether foreign items are present, each image is classified as "normal" or "intruded" at this point. Additional comments are added to the "intruded" photos in order to pinpoint the precise kind and location of the alien items. This could entail labelling the alien objects appropriately and drawing bounding boxes around them. The performance of the trained model is directly impacted by the precision and calibre of these annotations.

3. Yolov8 Model Building:

Building the YOLOv8 model for object detection comes next after the annotated dataset is prepared. A sophisticated deep learning model called YOLOv8 was created for real-time object detection. Because of its great speed and accuracy, it is perfect for dynamic areas like railway tracks where prompt detection is crucial. The YOLOv8 model is designed and set up to identify and locate alien objects in the pictures. For best results, this entails choosing the right architecture, specifying the input and output layers, and setting up hyperparameters.

4. Feature Engineering:

Finding and choosing the most pertinent features from the data that would enable the model to generate precise predictions is known as feature engineering. This entails prepping the input photos for object detection, making sure they are scaled and normalised, and perhaps using data augmentation techniques like rotation, flipping, and zooming to build a more reliable model. Features that are pertinent to the detection of alien objects, such as texture, shape, and colour patterns, may also be taken into consideration for improvement.

5. Model Training:

Using the annotated dataset, the YOLOv8 model is then trained. During training, the model gains the ability to recognise patterns in the pictures that match foreign items and to precisely classify and localise them. In order to ensure that the model learns the relationships between the input data and the intended outputs (object categorisation and localisation), the training procedure iterates over numerous epochs using backpropagation and optimisation methods to minimise the loss function. Here, the lightweight ResNet-tiny classification network—which is trained under the supervision of a bigger, more robust network—is made more accurate and efficient by using the Overhaul Knowledge Distillation technique.

6.Model Evaluation:

The model is rigorously evaluated using a different validation or test dataset following training. Evaluating the trained model's ability to generalise to new, unseen images is the aim. While mean average precision (mAP) is usually employed for object recognition tasks, metrics including accuracy, precision, recall, and F1-score are utilised to assess classification performance. To make sure the model operates effectively in real-time applications, evaluation metrics like inference speed and frames per second (FPS) are also essential.

7. Object Detection:

The model is utilised for object detection on fresh photos after it has been effectively trained and assessed. In this last stage, fresh railway photos are fed into the trained YOLOv8 model, which determines whether or not they contain foreign objects. When an image is labelled as "intruded," the model not only classifies the object but also localises it by classifying the sort of foreign object found and creating bounding boxes. It is anticipated that the model will operate in real-time, guaranteeing that it can continuously monitor and deliver precise findings for prompt action on railway tracks. From data collection to object detection, this procedure guarantees that the suggested system is precise and effective in identifying foreign items on railway tracks, hence enhancing operating effectiveness and safety.

6. TECHNIQUES USED IN PROJECT

6.1 EXISTING TECHNIQUE: -

- **Yolov5**

YOLOv5s, a cutting-edge single-stage object detector built for real-time detection applications, is the main algorithm used. YOLO (You Only Look Once) provides fast inference by dividing the input image into grids and predicting bounding boxes and class probabilities at the same time. YOLOv5s is a lightweight version with fewer parameters that is optimised for speedier processing. The model incorporates EfficientNet as a backbone network to enhance feature extraction. This network effectively scales network depth, width, and resolution, resulting in improved performance with fewer calculations. Additionally, the C3 module's Convolutional Block Attention Module (CBAM) improves the model's focus on pertinent spatial and channel-wise characteristics, which is especially advantageous for small object recognition.

By optimising anchor box dimensions (a priori frames), the K-means++ clustering method improves training stability and detection accuracy by producing superior bounding box recommendations that match the data distribution.

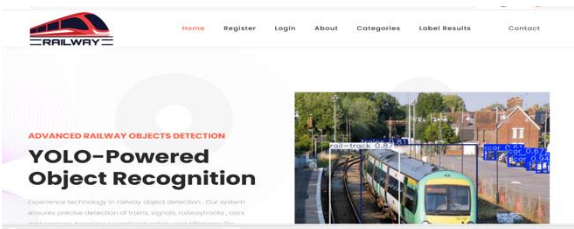
6.2 Yolov8 ALGORITHM USED:

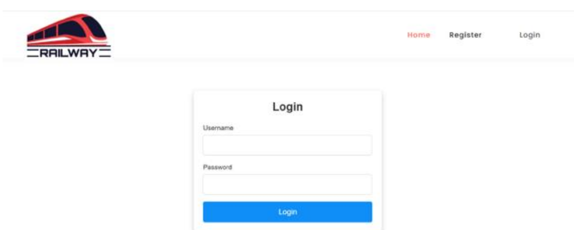
Yolov8 is used in this work to detect foreign items on railway rails accurately and in real-time. YOLOv8's anchor-free architecture, in contrast to previous iterations, improves its ability to identify small and asymmetrical objects. Additionally, it has a better head and backbone structure that makes it easier for the model to understand characteristics.

When compared to YOLOv5, YOLOv8 offers more speed and accuracy. In complicated contexts, it facilitates faster training, better data augmentation, and enhanced detection performance. It can also be deployed in real-time surveillance systems due to its lightweight architecture.

After a lightweight classifier filters the input photos, YOLOv8 is employed as the second stage in the suggested system. This two-step method maintains good accuracy while lessening the detection model's burden.

7. RESULTS





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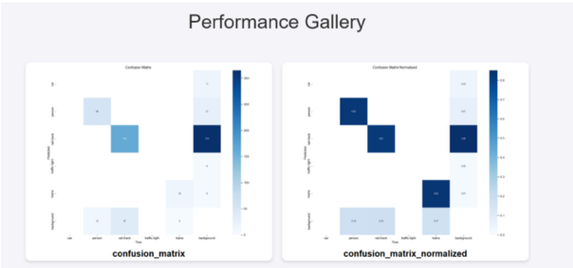

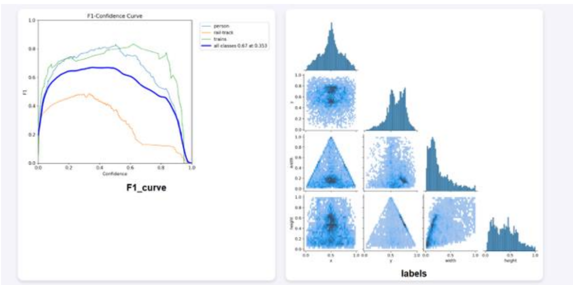

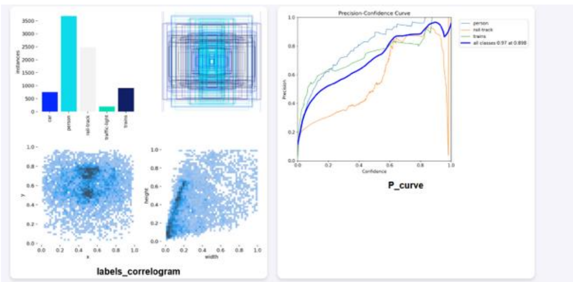

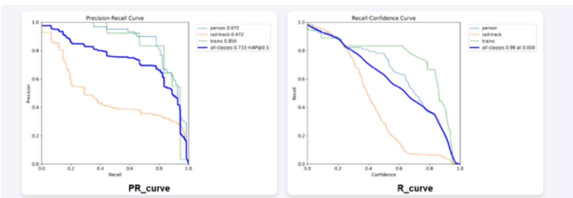

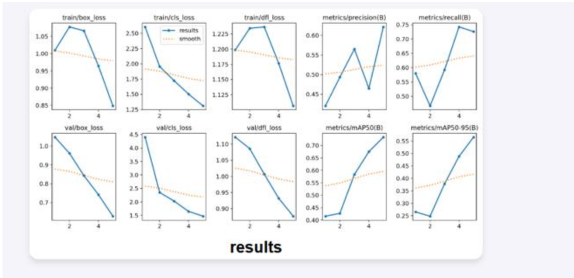

7. CONCLUSION

In summary, this study effectively illustrates the potential of utilising cutting-edge deep learning techniques, specifically the YOLOv10 object identification algorithm, to create a precise and effective real-time system for license plate recognition and safety helmet detection. The suggested method greatly improves workplace safety and vehicle monitoring in industrial and construction environments by tackling important issues including small item detection, ambient unpredictability, and multi-object recognition. Streamlined surveillance activities and better adherence to safety requirements are guaranteed by the integration of various functions into a single, cohesive structure. This system is an innovative response to the increasing need for intelligent automation in safety-critical settings because of its high performance, scalability, and possibility for additional improvements. The technology significantly contributes to the modernisation and safety of transport infrastructure by laying a solid foundation for upcoming enhancements and wider application across railway networks.

8. FUTURE ENHANCEMENT

The incorporation of a self-supervised learning framework to allow the model to continuously develop from real-world, unlabelled data would be a significant future improvement for the suggested railway foreign object intrusion detection system. Self-supervised techniques, in contrast to typical supervised approaches, may make use of the enormous volumes of sensor and video data gathered by surveillance systems without requiring manual annotations. The model would be able to adjust over time to shifting environmental circumstances, new obstacle types, and changing visual patterns on the railway lines thanks to its capacity for continual learning.

Moreover, the training dataset can be enhanced and model performance can be progressively improved by putting in place a feedback-based active learning loop, in which challenging or unclear detection cases are marked and sent for human review. In addition to lowering false positives and false negatives, this human-in-the-loop approach would keep the system informed of uncommon and unique infiltration incidents. This strategy could greatly improve the system's flexibility, accuracy, and dependability in dynamic, real-world railway contexts when paired with edge computing for on-site processing and quick reaction.

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