# Object Detection in Railway Line Using Artificial Intelligence Techniques

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**Abstract**
**Object detection in railway lines is a critical domain in the railway industry, aiming to enhance safety, operational efficiency, and the overall reliability of rail transportation. Various technologies and methods can be employed for object detection in railway lines, including but not limited to computer vision, LiDAR, radar, thermal imaging, and sensor networks. Machine learning and deep learning algorithms can be used for image and data analysis to classify and track objects such as trains, maintenance equipment, trespassers, or obstructions. Additionally, sensors and detectors can be strategically placed along the railway lines to capture critical data. This project delves into the advancements and challenges associated with object detection systems along railway lines. And aims to provide a holistic view of object detection in railway environments. It covers a wide range of topics, including the types of objects detected, the methods and technologies employed, real-world applications, and the future prospects of the field. Central to this system is the acquisition of data, primarily through high-resolution images and videos. These data sources originate from a variety of locations, including fixed cameras positioned along the railway tracks and cameras mounted on locomotives. This multi-source data collection is a crucial foundation for real-time monitoring and analysis, enabling the system to respond promptly to detected objects or potential obstacles. By combining data from multiple sources, the system provides a more comprehensive and accurate understanding of the railway environment, ensuring both safety and efficiency are prioritized.**

## Introduction
Intelligent transportation technologies have advanced quickly in recent years. Various types of machine learning algorithms are no longer bound as a vital part of the intelligent transportation system. An increasingly notable and dynamic area of research focuses on object detection for autonomous assistance in train driving and detecting faults. For recognizing traffic signs, pedestrians, and objects while operating a vehicle, computer vision is very important. One of the major problems resulting from the invention of the railway transportation system is the accidents with wild animals on the train tracks. Every year, many accidents happen on train lines and property damage. Some approaches for detecting objects on train tracks have been developed. Initially, in 2012, obstacles over rail tracks were tried to be detected using the Hough Transform method. In 2020, some researchers tried to detect the objects on the train line using the single-shot detection method. In 2021, there was a semi-supervised convolutional auto-encoder-based method to detect objects on train tracks. In 2022, there was YOLO V4 for detecting objects in the train line area. But all of this is able to detect the objects on the train track area. But the square-shaped detection bounding box bears the possibility of detecting the objects outside the train track. Which sometimes creates the opposite outcome: sometimes, the animals jump into the train track from the tracks outside while the train buzzes its horn. To avoid these complicated issues, there needs to be a system that is able to detect objects between the only two train lanes of a track. Because of this, early detection of objects can lower the number of accidents. Here we propose a system that can detect any objects only between the train lanes. Our assisted driving system's primary objective is object recognition while the train operates at a speed of under 50 kph. In this study, we first detected the train line. After detecting the train line, we assigned the region of interest as the detected train line. Thirdly, we trained our system to detect any object between the train lanes or the detected train line area. Here we used mainly the Mask RCNN algorithm to detect both the train line and to detect the object in the train track.

## Literature Review

There are some previous research works where the authors tried to detect the objects on the train track; the detection frame is a square ROI, which is why sometimes the system detects the object that is out of the train track and at a safe distance. Sometimes it's good, but in wildlife or domestic animal cases, it sometimes may occur the opposite, like the animals entering the track instead of staying far away from it. Due to this reason, in our system, we first detected the only train line. Then we detect the object if there's any. A Mask RCNN algorithm was employed for both detecting systems. The architecture diagram of figure 1 shows that the input image is passed through a backbone CNN, such as Reset, to extract features. These features are then used to construct a feature pyramid that is used by a Region Proposal Network (RPN) to generate object proposals. The object proposals are then passed through two parallel branches. The first branch performs ROI Align to extract fixed-length feature maps for each proposal. These feature maps are then used for object classification and bounding box regression. The second branch, called the mask head, takes the ROI-aligned feature maps and performs several convolutional layers to generate a binary mask for each object proposal. In order to enhance the system's accuracy, a solitary convolutional layer comprising 256 filters and a $3 \times 3$ kernel was incorporated into the existing layers of the backbone. The final output of Mask R-CNN includes the object class and bounding box predictions, as well as a binary mask for each object. The binary mask indicates which pixels in the object proposal belong to the object and which do not. For each sampled ROI, a multi-task loss is applied by equation 1 and the Loss function of RPN

## Research Methodology

In the training and testing steps, a pre-trained model was selected to use as the base for the Mask R-CNN architecture. Common choices include the ResNet family of models, which are designed for image classification tasks. After selecting the base model, there was transfer learning to adapt it to specific object detection and segmentation tasks. This typically involves freezing the weights of the lower layers of the model and training only the higher layers, which are responsible for object detection and segmentation. From the different augmentations, we selected the valid one, trained the final model, and got the weights. In the testing portion, we performed the prediction on the split test set and printed the test set result.

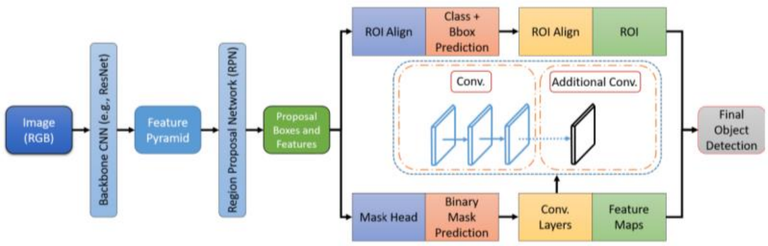


**FIGURE 1.** **Framework of modified Mask RCNN algorithm.**

The system flow diagram consists of multiple important steps are shown in figure 4. From frame detection to object detection on the specific trained region of interest is sequenced in a processing method. After adapting the base model to the task, there need to fine-tune the entire model on the dataset to further improve its accuracy. Throughout the training process, the hyperparameters of the model need to be carefully tuned to ensure optimal performance. This can involve adjusting parameters such as the learning rate, batch size, and regularization strength. Finally, there needs to be an evaluation of the model's performance on a separate validation dataset to ensure that it is generalizing well to new images. The training process was time-consuming and computationally intensive, but with careful attention to detail and hyperparameter tuning, the system achieved state-of-theart performance on object detection and segmentation tasks using Mask R-CNN. In this step, the system will detect the blue mask from the frame to specify the region of interest. The region of interest, or polygon, is the detected train track. After that, the RGB conversion will be applied again to improve the accuracy of the detection model.

## Conclusion

To reduce the number of wildlife deaths and unwanted train accidents on train lines, there's a need for a smart automated system to detect unwanted objects on train tracks and warn the concerned authority timely. Machine learning techniques can be used for object detection on train lines, providing enhanced safety and operational benefits. For this reason, this paper proposes a mask-RCNN-based system to detect the train line and detect unwanted objects on the train line. The system, compared to other previous approaches, performed way better, and this study is more focused on wildlife safety on train lines. That's why we made the dataset have more animals as objects. The system can be used for smart and automated train driving assistants and can play a vital role in reducing accidents on train lines.

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