Vision Based Few-Shot Railway Intrusion Detection Via Dual Detector and Contrastive Learning

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ABSTRACT

Railway transportation systems require reliable monitoring mechanisms to ensure track safety and prevent accidents caused by unexpected obstacles. The presence of humans, animals, or objects on railway tracks can lead to dangerous situationsandoperationaldisruptions.Recent improvements in computer vision have allowed automated surveillance systems to identify objects as they happen in real time. A vision-based system is developed to detect railway intrusions using a dual- detector architecture combined with few- shot learning and contrastive learning techniques.

The system takes pictures from a monitoring camera and checks for any signs of someone entering the area around the railway tracks. When the system detects something entering, like a person, animal, or object, it sends an alert using the built-in controller and saves the details of the event for later review. By using few-shot learning methods, the system can better detect things even when there isn't a large amount of training data available. Tests show that the new method works well at detecting intrusions and performs better than older ways of using video to monitor things [1]-[4].

Keywords: Railway intrusion detection, few-shot learning, contrastive learning, dual detector, railway safety.

INTRODUCTION

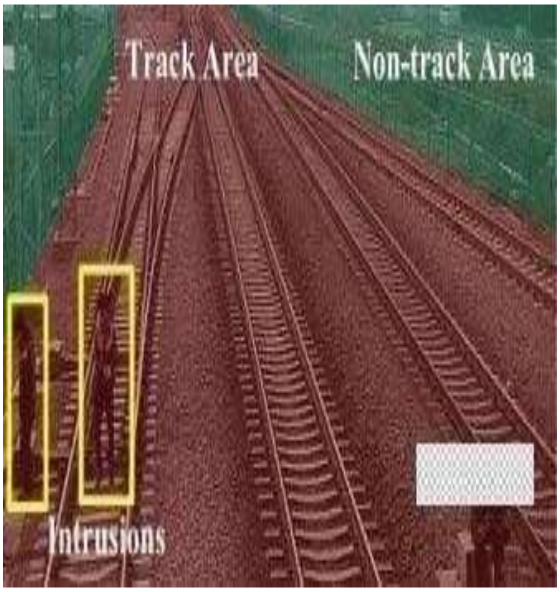
Railway transportation plays a vital role in modern transportation systems by enabling efficient movement of passengers and goods. Railway tracks often face safety problems because people, animals, or other unexpected things may walk or fall onto the tracks. Such intrusions can lead to serious accidents, train delays, and operational disruptions. So, creating dependable railway monitoring systems has become an important requirement for improving railway safety.

Traditional railway surveillance systems mostly use either manual watching or sensor methods like infrared and vibration sensors. These systems can detect basic signals of intrusion but often struggle to accurately differentiate between real threats and environmental disturbances. They might also give warnings when there's nothing really there, because of things like wind or other outside noises.

Recent advancements in computer vision and deep learning have enabled automated systems capable of monitoring environments and detecting objects using visual data. Modern object detection frameworks like YOLO are commonly used in real-time vision systems because they can detect multiple objects in a single image while maintaining high processing speed and reliable detection accuracy. [1]. Further improvements in deep learning architectures have enhanced both the accuracy and efficiency of object detection in surveillance applications [2]. In addition, region-based detection methods such as Fast R-CNN improve object localization accuracy by using region proposal mechanisms to identify potential object locations within an image [3].Despite these advancements, many deep learning models still require large training datasets to achieve reliable detection performance. In real railway monitoring situations, it's usually hard to gather a lot of labeled intrusion data. To solve this problem, some learning methods have been developed that let models learn effectively even when they only have a small number of examples [5]. Contrastive learning methods help improve how well features are represented by understanding the similarities between different image examples, which leads to better classification results when working with small datasets [6].

A vision-based railway intrusion detection system is developed to monitor track areas and identify intrusions even when only a limited number of training samples are available. It uses a dual-detector setup along with contrastive learning methods. The system identifies intrusions such as humans, animals, or foreign objects on railway tracks and generates alerts to enhance railway safety.

Fig.1: Railway Track Monitoring Region



OBJECTIVE

To develop a vision-based monitoring system that uses camera input to detect the presence of humans, animals, or foreign objects on railway tracks.

To implement a dual-detector architecture for improving the accuracy and reliability of object detection in complex railway environments.

To apply few-shot learning techniques to enable the detection model to operate effectively even when limited training data are available.

To utilize contrastive learning methods to enhance feature representation and improve object classification performance.

To generate an alert mechanism using an embedded system that activates a buzzer and displays a warning message when an intrusion is detected.

LITERATURE SURVEY

Computer vision methods are extensively used for automated monitoring and object detection in surveillance applications. The object detection framework YOLO was introduced by Joseph Redmon and processes an entire image using a single neural network, enabling the system to identify multiple objects simultaneously with real-time performance [1]. This framework improved detection speed compared with traditional region-based object detection methods.

Subsequent improvements such as YOLOv3 introduced multi-scale feature extraction techniques that enable detection of objects with different sizes more effectively [2]. Girshick, which enhanced object. Another significant advancement is Fast R-CNNproposed by Ross Girshick, which improves object localization accuracy by extracting features from region proposals generated within an image [3].

In railway safety monitoring systems, deep learning models have been applied to identify obstacles, pedestrians, and animals appearing on railway tracks. Chen and his team demonstrated that convolutional neural networks can effectively detect obstacles on railway tracks using imagebased monitoring systems [4].

However, several deep learning approaches depend on large amounts of labeled training data to achieve reliable performance. To overcome this limitation, few-shot learning approaches were developed to perform classification tasks using only a limited number of training samples. Snell and his team proposed Prototypical Networks, which allow models to generalize effectively from limited training data [5].

Contrastive learning techniques enhance feature representation by reducing the distance between similar samples while increasing the separation between dissimilar samples in the feature space [6]. These approaches have demonstrated improved performance in several computer vision applications under varying environmental conditions.

Recent advancements in deep learning architectures and large-scale datasets have further improved the accuracy of visual object recognition systems used in surveillance environments [7], [8].

EXISTING METHOD

Traditional railway intrusion monitoring approaches mainly rely on sensor-based technologies such as infrared detectors,vibration sensing devices, and manual surveillance to identify possible intrusions near railway tracks. While these techniques are capable of detecting the presence of objects near railway tracks, their performance is often limited and they may produce incorrect alerts due to environmental factors or noise.

With recent developments in computer vision, many monitoring solutions have started using deep learning–based object detection approaches to analyze images captured by cameras. Detection frameworks such as YOLO and region-based detection models have demonstrated effective realtime object recognition capabilities [1], [3]. However, many deep learning detection models depend on large labeled datasets to achieve stable and reliable performance, which is often difficult to obtain in real railway monitoring environments.

In real railway environments, collecting extensive datasets that include various intrusion situations is often challenging. Because of this limitation, conventional deep learning approaches may not perform well when encountering uncommon or previously unseen objects on railway tracks. Therefore, more advanced detection techniques are required that can operate efficiently even when only a limited number of training samples are available [5].

PROPOSED METHOD

The proposed system continuously monitors the railway track region using a camera that captures video frames in real time. The captured frames are processed through computer vision techniques implemented using the OpenCV framework along with deep learning–based detection algorithms.

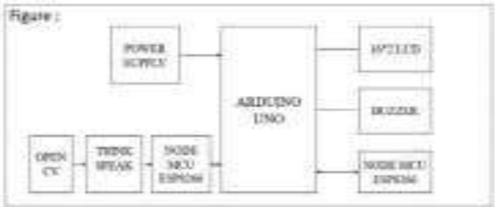
The detection process follows a dualdetector architecture. The first detector is responsible for identifying potential objects appearing within the monitored area by applying a deep learning object detection model. After the initial detection stage, a second detector refines the classification by analyzing feature similarities using contrastive learning techniques.

Contrastive learning improves the representation of features by minimizing the distance between similar samples while increasing the separation between different classes in the feature space [6]. This mechanism enables the system to distinguish various intrusion categories such as humans, animals, and foreign objects, even when the available training dataset is limited.

When an intrusion is detected, the system activates an alert through an embedded microcontroller. A buzzer generates an audible warning, while the detected event information is displayed on an LCD module. In addition, the system can store event data through a wireless communication module to support monitoring and further analysis.

BLOCK DIAGRAM

Fig.2: Block diagram of the proposed Railway Intrusion detection system



Performance Evaluation and Numerical

Results

For Example, The system was tested under different intrusion scenarios including human presence, animals, and foreign objects on the railway track. A total of 40 test samples were evaluated to measure the detection performance. The system correctly identified 38 intrusion events, resulting in an overall detection accuracy of 95%.

Accuracy = Correct Detections / Total Test Cases*100

Table 1: Intrusion Detection Test Results

Test Scenario	Total Tests	Correct Detections
No Object on Track	10	9
Human Intrusion	10	10
Animal Intrusion	10	9
Object detection	10	10
Total	40	38

Accuracy = 38 / 40 * 100

=95%

CONCLUSION

A system that uses vision to detect railway intrusions was created to find any unwanted items on the railway tracks. The system uses a camera to watch the track area and then looks at each picture it takes. It uses a special method that mixes two types of detection and learning from features to process these pictures. The model we created can detect various kinds of intrusions, like people, animals, and other things that might enter the area around the railway tracks. The system works well even when there are not many training examples available, thanks to methods that handle situations with limited data. When the system detects an intruder, it sends an alert using the built-in hardware to show there might be a problem. The results show that the system helps find unsafe track conditions and supports railway safety by automatically watching the tracks with cameras [1], [6], [7].

REFERENCES

[1] J. Redmon, S. Divvala, R. Girshick, and

A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779– 788, 2016.

[2] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv preprint arXiv:1804.02767, 2018.

[3] R. Girshick, "Fast R-CNN," Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 1440–1448, 2015.

[4] Z. Chen, X. Wang, and L. Zhang, "Deep Learning-Based Railway Obstacle Detection Using Image Processing Techniques," IEEE Access, vol. 7, pp. 163–172, 2019.

[5] J. Snell, K. Swersky, and R. Zemel, "Prototypical Networks for Few-Shot Learning," Advances in Neural Information Processing Systems (NeurIPS), pp. 4077– 4087, 2017.

[6] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A Simple Framework for Contrastive Learning of Visual Representations," Proceedings of the International Conference on Machine Learning (ICML), pp. 1597–1607, 2020.

A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Advance in Neural Information Processing Systems,

pp. 1097–1105, 2012.

[7] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778, 2016

