**LITERATURE SURVEY**

**Y. Li, Y. Xia, Z. Wang, Z. X u and X. Li, “Railway Detection from Airborne LiDAR Data Using Deep Learning Networks,” Remote Sensing, 11(2), pp.184, 2019.**

# Images gathered from different satellites are vastly available these days due to the fast development of remote sensing (RS) technology. These images significantly enhance the data sources of change detection (CD). CD is a technique of recognizing the dissimilarities in the images acquired at distinct intervals and are used for numerous applications, such as urban area development, disaster management, land cover object identification, etc. In recent years, deep learning (DL) techniques have been used tremendously in change detection processes, where it has achieved great success because of their practical applications. Some researchers have even claimed that DL approaches outperform traditional approaches and enhance change detection accuracy. Therefore, this review focuses on deep learning techniques, such as supervised, unsupervised, and semi-supervised for different change detection datasets, such as SAR, multispectral, hyperspectral, VHR, and heterogeneous images, and their advantages and disadvantages will be highlighted. In the end, some significant challenges are discussed to understand the context of improvements in change detection datasets and deep learning models. Overall, this review will be beneficial for the future development of CD methods.

**Y. Li, Y. Wu and Y. Xia, “Railway track detection from high- resolution satellite images using deep learning,” Remote Sensing, 12(17), pp. 2776, 2020.**

The detection of obstacles at rail level crossings (RLC) is an important task for ensuring the safety of train traffic. Traffic control systems require reliable sensors for determining the state of anRLC. Fusion of information from a number of sensors located at the site increases the capability for reacting to dangerous situations. One such source is video from monitoring cameras. This paper presents a method for processing video data, using deep learning, for the determination of the state of the area (region of interest—ROI) vital for a safe passage of the train. The proposed approach is validated using video surveillance material from a number of RLC sites in Poland. The films include 24/7 observations in all weather conditions and in all seasons of the year. Results show that the recall values reach 0.98 using significantly reduced processing resources. The solution can be used as an auxiliary source of signals for train control systems, together with other sensor data, and the fused dataset can meet railway safety standards.

**L. Chen, H. Wang, J. Wang, and Z. Wei, “A Railway Track Detection Method Based on Deep Learning,” In 2020 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM), pp. 156-159, 2020.**

Based on the design of the test data channel of rail flaw detection car, the generation principle of B-scan data and the classification of rail flaw, the differences between the rail flaw identification by rail flaw detection car and the common image recognition are analyzed. The detection data are regarded as the images superimposed by the binary matrices of 16 channels. A deep learning structure is designed which includes 1 input layer, 3 convolutional layers, 3 pooling layers, 2 fully connected layers and 1 output layer. By noise and channel preprocessing, the "object detection" problem of rail flaw is converted to the "classification" problem. The artificial rail flaw detection data of some place are expanded and used as training sets to obtain the intelligent recognition model of rail flaw based on deep learning. The artificial rail flaw detection data of another place are used as test data to evaluate the recognition effect of the model. Comparing the model identification results with those obtained from the existing system of rail flaw detection car and manual analysis, the comparison results show that the intelligent recognition model of rail flaw based on deep learning is superior to the existing system of rail flaw detection car in the accuracy rate and false alarm rate. The model meets the index requirements of manual analysis and improves the accuracy. © 2018, Editorial Department of China Railway Science. All right reserved.

**L. Sun, W. Wang, Y. Lu, Z. Hu nad B. Shang, “An automatic approach to railway track detection using improved Faster R-CNN,” IEEE Access, 7, pp. 81994-82005, 2019.**

Overhead contact systems (OCSs) are the power supply facility of high-speed trains and plays a vital role in the operation of high-speed trains. The dropper is an important guarantee for the suspension system of the OCS. Faults of the dropper, such as slack and breakage, can cause a certain threat to the power supply system. How to use artificial intelligence technologies to detect faults is an urgent technical problem to be solved. Because droppers are very small in whole images, a feasible solution to the problem is to identify and locate the droppers first, then segment them, and then identify the fault type of the segmented droppers. This paper proposes an improved Faster R-CNN algorithm that can accurately identify and locate droppers. The innovations of the method consist of two parts. First, a balanced attention feature pyramid network (BA-FPN) is used to predict the detection anchor. Based on the attention mechanism, BA-FPN performs feature fusion on feature maps of different levels of the feature pyramid network to balance the original features of each layer. After that, a center-point rectangle loss (CR Loss) is designed as the bounding box regression loss function of Faster R-CNN. Through a center-point rectangle penalty term, the anchor box quickly moves closer to the ground-truth box during the training process. We validate the improved Faster R-CNN through extensive experiments on the VOC 2012 and MSCOCO 2014 datasets. Experimental results prove the effectiveness of the proposed network combined with attention feature fusion and center-point rectangle loss. On the OCS dataset, the accuracy using the combination of the improved Faster R-CNN and ResNet-101 reached 86.8% mAP@0.5 and 83.9% mAP@0.7, which was the best performance among all results.