# Fault Detection and Sematic Segmentation on Railway Track

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***Abstract:*** IoT-based ABSTRACT Track quality and train operating safety depend on routine inspections of track components. According to statistics from the Federal Railroad Administration (FRA), train accidents in the United States are primarily caused by the failure of track components. Existing technologies, such as fault detection and fault segmentation, have been used to increase efficiency. However, these models sometimes fail when dealing with small or broken cracks. To address this issue, we suggest implementing a fusion model that uses a deep convolutional neural network for fault detection and semantic segmentation on railway lines. The ResNet50 network is used for fault identification in this model, while the Deep Residual U-Net network is applied for semantic segmentation. The identified defects are isolated, and decisions can be made from resulting binary image segments on whether to inspect or disregard detected faults. These defects include damages observed on railway tracks and any absent or damaged components such as spikes, clips, and rails. Comprehensive tests carried out on a track dataset obtained from the Kaggle repository demonstrate that the suggested approach is capable of accomplishing the following: 1) surpassing current leading models by achieving 94.3% mean average precision (mAP) for fault detection and 79 frames/sec, and 2) achieving 95.6% accuracy in semantic segmentation. Therefore, this fusion model helps inspect tracks by detecting and segmenting faults, thereby reducing derailment cases and other railroad-related accidents.

***Keywords: Deepfusion, deep learning, fault detection, railroad safety, semantic segmentation.***

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## I. INTRODUCTION

In 2018, the FRA safety database documented 546 incidents resulting from track deficiencies, underscoring the critical need for regular inspections of railway track components to maintain safety and operational efficiency [16], [17]. These accidents resulted in a financial loss of almost $97 million and had significant societal consequences. Of these occurrences, a total of 48 were attributed to the absence of spikes, clips, and damaged rails, resulting in an estimated $10 million in financial losses. The FRA requires routine inspections of railway tracks across the United States to ensure preventive safety measures. However, despite advancements such as track geometry

measurement, inspecting for missing track components still requires a significant amount of manual effort and consumes a considerable amount of time The proposed work modifies and trains a recently devel oped deep fusion model to meet the specific needs of railway track inspection. The objective is to enable efficient and accurate examination of railway track components in real-time using a single Graphical Processing Unit (GPU). After that, the created models are assessed and contrasted with the most advanced models currently available. Fig. 1 provides an overview of the process. The suggested model aims to develop a fusion model using a deep CNN to detect faults on railway tracks. These faults include damages present on the track and missing or broken components (Spike, Clip, and Rail). The challenges with railroad track inspection are that the work must be completed quickly and the train crew's tasks must be reasonably simple. Taking into account the engineering challenges and motivated by the successful implementations of SSD ResNet50 and Deep Residual U-Net, the cutting-edge object recognition and semantic segmentation algorithms in deep learning, respectively, the objective of this work is to develop a minimally compu tationally demanding, accurate, and rapid track inspection system. This paper outlines the creation of a framework for the real-time examination of components used in railway tracks. The system utilizes two powerful algorithms for object identification and semantic segmentation, which are combined to enhance the accuracy and effectiveness of the inspection workflow.

## II. METHODOLOGY

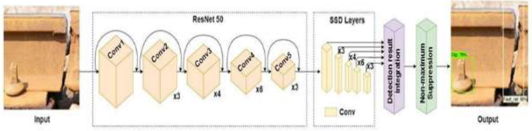

**Fig 1: The architecture of SSD ResNet50 used for fault detection.**

An activity of most importance is the diligent supervision of railway tracks since a failure to monitor them might result in loss of life. Hence, the proposed model helps to inspect the tracks by detecting faults on the railway tracks with the help of a deep fusion model that integrates detection and segmentation. Detection is performed first, followed by segmentation. If the order is altered, with segmentation preceding detection, fractures in the track may lead to misjudged segmentation results, potentially identifying multiple cracks. Additionally, the segmented image, being binary, cannot be utilized further for detection purposes.

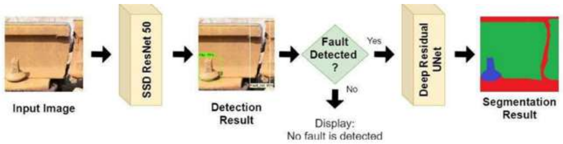

**Fig 2: The expected outcomes from the deep fusion model.**

The SSD RESNET50 The Single Shot Detector (SSD) model comprises a two part structure: the backbone and the SSD head. Algorithm 1 provides the pseudocode for object detection performed by the SSD ResNet50 algorithm. The backbone of the system is generated using a pre-trained image classification network, which then serves as a feature map extractor. The classification layers are removed from the network, leaving only the feature maps. The SSD head consists of convolution layers stacked on top of the feature maps. These convolution layers help identify the objects within the images.

## III. WORKFLOW OF DEEP FUSION MODEL

The Deep Fusion model integrates the SSD ResNet-50 framework with the Deep Residual U-Net framework. As depicted in Fig. 4, the model begins by feeding the input image into the Detection model to acquire the detection outcomes. These detection results serve as input for the Segmentation model, which produces the final segmented output image for display.

The system integrates with an Android app to show emergency alerts and location. Using Google Cloud Messaging (GCM), it sends push notifications, and SMS alerts are triggered to inform emergency contacts. The module also shares the GPS location to assist in quick response and rescue operations.

## IV. IMPLEMENTATION

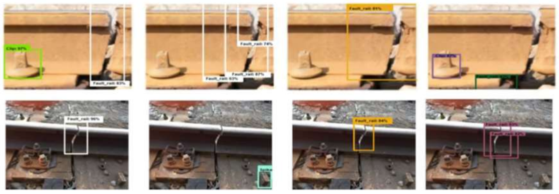

**Fig 3: Fault detection results using various deep neural network models.**

After detection of an accident or it detects whether any of the medical or criminal emergency button is pressed, the system sends the vehicular emergency location in the form of a Mobile SMS to the registered phone numbers of the family, police station, rescue team, hospital, etc

## V. DETAILS OF EMERGENCY TYPE

The dataset comprises images of both defective and non-defective components of railway tracks, collected from the Kaggle repository. It includes images of railway tracks with components such as clips, spikes, and rail surfaces.

The dataset contains a total of 1500 images. Data augmentation techniques like cropping, padding, and horizontal flipping were applied to the collected images to enable the proposed model to train on a larger number of images. This augmentation was conducted using the Rob flow tool. To detect objects representing faulty railway components, the images were annotated with the corresponding class names using a labeling tool. For each annotated image, a corresponding XML file is generated that contains the bounding box dimensions and the class name. On the other hand, to perform semantic segmentation, firstly, the images need to be labeled using the LabelMe tool. For each segmented image, a corresponding JSON file containing the details of the segmented region and the class name is generated. Then, the ground truth images need to be created for every segmented image. Once the annotation process is completed, it is necessary to build masks for all the labelled images. This is accomplished with the use of Python code. Afterward, data augmentation techniques such as cropping.

## VI. RESULT ANALYSIS

The system successfully collected real-time data from all connected sensors. Many models can be used for object detection purposes [28], including Mobile Net, Efficient, and SSD ResNet-50. The choice of model should be based on the application. Consistency in model evaluation is ensured by using the same dataset for both training and testing each model. Subsequently, performance metrics such as accuracy, precision, and recall are calculated, and the approach with the highest accuracy is selected for further detection tasks.location data with each alert, ensuring quick response.

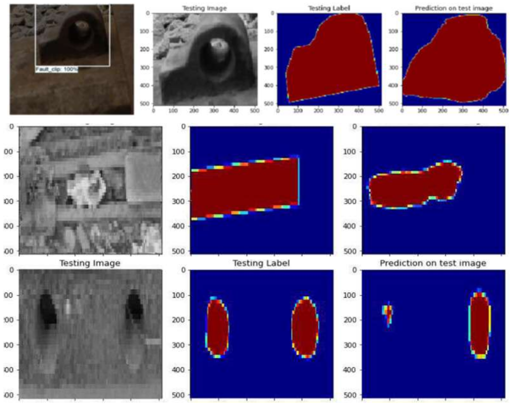

**Fig 4: Outcomes of deep fusion model.**

IoT- illustrates the graph plotted to infer the loss and the learning rate. The SSD ResNet-50 was trained over 22,000 steps, and it is observed that the loss gradually decreases as the number of steps increases. This process is repeated for all the models namely SSD ResNet-50, SSD MobilenetV2, SSD EfficientDet, and YoloV4 Darknet. The results of all these models will be discussed using the confusion matrix, which is shown in To compute performance metrics for the comparative study, import necessary packages like pandas and NumPy. Utilize the ‘crosstab()‘ function from pandas to construct the confusion matrix as depicted in Fig. 8 for each model, based on their respective Excel sheets. The confusion matrix comprises two axes: the horizontal axis denotes the ‘‘Actual Class’’ and the vertical axis represents the ‘‘Predicted Class’’.Extract features including TP, FP, TN, and FN from the given.

U-Net, where the first graph represents loss and the second graph shows accuracy. It was trained over 150 epochs. After training completion, testing was conducted on the pre-trained models. The segmentation results are illustrated in Fig displaying the segmented regions, which include fault clip and fault rail. Below are the test values and predicted values for each class on the validation set of Deep Residual U-Net. Using this data, the Intersection Over Union (IoU) for each class was calculated. Table 4 presents the evaluated values of the Deep Residual U-Net model for the dataset. It is estimated that the model has a mean IoU of 91% and an accuracy of 95%.

## VII. CONCLUSION

The proposed approach is structured into three main phases. The detection process begins with SSD ResNet-50, which requires the development, enhancement, and annotation of the Pascal VOC dataset to facilitate training. Following data preparation, the SSD ResNet-50 model undergoes training and testing using input images. The second phase focuses on segmentation using Deep Residual U-Net, where data processing mirrors that of SSD, but includes mask generation. The final phase integrates both models seamlessly. If a fault is detected by SSD ResNet-50, then that fault will be further segmented by Deep Residual U-Net after extracting the bounding boxes of the detected faults. Thus, the faults present in the tracks are segmented and the final segmented image obtained as the output of our proposed work.

In future research, the aim is to identify faults live videos and conduct detailed examinations of any detected cracks, including analyzing their dimensions such as length, width, and height. Additionally, enhancing the dataset may involve capturing real-time images and extracting frames from live video stream

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