Autonomous Rail Surface Defect Detection

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The Autonomous Rail Surface Defect Detection project aims to enhance railway safety through the use of unmanned aerial vehicles (UAVs) for detecting rail surface defects. Using the RSD_UAV dataset, the project developed an optimized DeepLabv3-plus model with a ResNet-18 backbone and CBAM, achieving a mean Intersection over Union (mIOU) of 84.97% and a mean accuracy of 92.60%. The dataset, containing 13,053 images of various rail defects, was collected in Columbia, SC, and rigorously processed for model training. The system's performance was tested across different UAV flight patterns, revealing consistent defect detection but with reduced accuracy as the UAV's altitude increased. Optimal detection occurred between 3 to 9 ft above the rail, with accuracy decreasing at higher altitudes or lateral distances from the rails. This research underscores the potential of UAVs and deep learning models in advancing railway inspection and safety.</td></tr>
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List of Abbreviations

CBAM	Convolutional Block Attention Module
mIOU	Mean Intersection Over Union
RSD	Rail Surface Defects
SVM	Support Vector Machines
UAV	Unmanned Aerial Vehicles
USDOT	U.S. Department of Transportation
UTCRS	University Transportation Center for Railway Safety

Disclaimer

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1. SUMMARY

The Autonomous Rail Surface Defect Detection project aims to improve railway safety by employing unmanned aerial vehicles (UAVs) to detect rail surface defects, as illustrated in Figure 1. Utilizing a customized dataset, the RSD_UAV dataset, the project developed an enhanced DeepLabv3-plus model integrated with advanced image processing techniques and machine learning algorithms, including a lightweight ResNet-18 backbone and a Convolutional Block Attention Module (CBAM). This model enabled efficient and accurate rail surface defect detection, achieving a mean Intersection over Union (mIOU) of 84.97% and a mean accuracy (mAccuracy) of 92.60%.

Figure 1: Rail surface defects

Data for this study was collected over several rail sections in Columbia, SC, encompassing a variety of typical rail defects. This dataset, comprising 13,053 images, was rigorously processed and augmented to train the model under different conditions. The robustness of the developed system was evaluated across multiple UAV flight patterns, demonstrating reliable rail surface defect detection in all tested scenarios, though with varying degrees of defect detection efficacy based on the UAV's height and lateral distance from the rails. Further empirical evaluations demonstrated that the model effectively detects rail surface defects (RSDs) when the UAV is operated between 3 ft and 9 ft above the rail surface. However, as the UAV's altitude increases to

12 ft or more, the detection accuracy decreases, indicating only partial detection of RSDs. Additionally, when the UAV is positioned 5 ft laterally from the rail surface, the detection of RSD is significantly compromised at a height of 3 ft; however, elevating the UAV slightly improves this detection.

Throughout various experimental setups, the rail surface was consistently detectable under all tested conditions. The creation and utilization of the RSD_UAV dataset, combined with the demonstrated performance of the detection system, represent pioneering contributions to the field of railway inspection and maintenance. This research highlights the potential of UAV-imagery combined with advanced deep learning models for improving the safety and maintenance planning of railway track.

2. BACKGROUND

As the speed and load capacities of trains have increased significantly, the safety demands of railway operations have increased accordingly. Influenced by factors such as temperature, moisture, and load, the track surface may gradually develop defects of varying degrees. If not promptly addressed, these defects can deepen, significantly elevating the risk associated with train operations. Conventionally, railway inspections have relied on manual checks. However, such inspections are subjective, inefficient, time-consuming, costly, and susceptible to adverse conditions. Thus, the automation of rail surface defect detection holds considerable practical value and is of significant academic interest.

Traditional image-processing-based defect detection algorithms typically commence by extracting features of the target, followed by defect identification based on these features. Common feature extraction methods include wavelet filtering [1], Fourier transforms [2], and local binary patterns [3]. Once the features of the defect area are extracted, defect identification is performed using techniques such as Bayesian networks [4], k-nearest neighbors [5], and Support Vector Machines (SVM) [6]. Nonetheless, the effectiveness of these methodologies is considerably constrained by the subjective nature of feature design and extraction, and their performance is susceptible to environmental variables like lighting and noise.

With the advent of deep learning and convolutional neural networks in the realm of image processing [7], various target detection algorithms [8] have been adapted for use in defect detection tasks. For instance, Zheng et al. [9] introduced a deep learning algorithm that incorporates a squeeze-and-expand mechanism, designed for rapid defect detection on copper-clad boards. Similarly, Badmos et al. [10] employed a pre-trained VGG19 network for lithium-ion battery electrode defect detection. However, while these methodologies are capable of classifying defect images, they fall short in locating the exact locations, thereby limiting their applicability for tasks requiring precise defect localization. In general, the inspection of rail surface defects presents several challenges:

1. The developed model needs to adapt to the random noise inherent in complex field conditions, such as reflections from other track components.
2. The model must effectively manage imbalanced instances due to the small ratio of defect area to the overall rail surface area, which can complicate model training.
3. State-of-the-art (SOTA) models, generally designed for general detection applications, often require substantial computational resources and may not deliver high accuracy in specialized railroad scenarios.
4. Many of these models underperform in edge segmentation of rail surfaces.
5. There is a notable scarcity of datasets specifically related to rail surfaces, complicating the development and training of effective detection models.

3. OBJECTIVES AND SCOPE

This project aims to establish a specialized RSD_UAV database and develop a tailored model for rail surface defect detection with UAV-imagery. During the data collection process, factors such as different heights from the rails and different lateral ranges were taken into account to understand the influence of UAV flight. The dataset is rich and has practical value. The database contains a total of 13,053 images, divided into 70% for the training set, 15% for the verification set, and 15% for the test set. Next, the improved DeepLabv3-plus model was trained using the new RSD_UAV dataset to inspect RSD with high accuracy and efficiency. To accelerate inference speed without sacrificing accuracy, the lightweight ResNet-18 backbone was adopted. The model was enhanced to focus on critical feature representations by integrating the Convolutional Block Attention Module (CBAM) into the decoder part of the improved DeepLabv3-plus model. The

Lovász-Softmax loss was implemented to address severe data imbalance. The improved model achieves the best performance based on evaluation metrics and visualizations.

4. METHODOLOGY

4.1 Data Collection

In this project, the RSD_UAV data was collected on Sumter St, Columbia, SC 29201 (coordinates: 33.987932, -81.025855), as depicted in Figure 2. This section of the railway is located in the downtown area, where large freight trains frequently pass and which is near a crossroads, resulting in many typical rail surface defects. As shown in Figure 3, the Parrot ANAFI USA, a powerful American-made drone, was used to collect the RSD_UAV data. The drone, when unfolded, measures 242 x 315 x 64 mm and weighs 315 g. It has a maximum speed of 55 km/h, a maximum vertical speed of 4 m/s, and can resist winds up to 50 km/h.

Figure 2: The area of RSD_UAV data collection (Google Map)

In the experimental plan for data collection, two variables were established: the flying height of the drone and the lateral distance of the drone's flight path from the track. The flight heights are set at 3 ft, 6 ft, 9 ft, and 12 ft, respectively. Lateral distances are set at 0 ft (i.e., flying directly above the rails) and 5 ft, creating a total of eight different conditions. Roboflow was employed for data labeling. The RSD_UAV dataset includes two segmentation classes, "railsurface" and "defects." After labeling all the RSD_UAV data, preprocessing and augmentations were applied to increase the robustness of the dataset. Ultimately, the RSD_UAV dataset was successfully built and contains a total of 13,053 images. It is divided into 70% for the training set, 15% for the verification set, and 15% for the test set.

4.2 Model Training

The improved DeepLabv3+ model (Figure 3) was trained using the new RSD_UAV dataset to inspect RSD with high accuracy and efficiency. To accelerate inference speed without sacrificing accuracy, the lightweight backbone, ResNet-18, is adopted. The model focuses on critical feature representations by integrating the Convolutional Block Attention Module (CBAM) with the decoder part of the improved DeepLabv3+ model. Lovász-Softmax loss is used to address severe data imbalance. This model develops an effective decoder to enhance the final segmentation results with refined object boundaries. The resolution of extracted encoder features can be adjusted with atrous convolution, and both the Xception model and depthwise convolution are adopted for better segmentation performance.

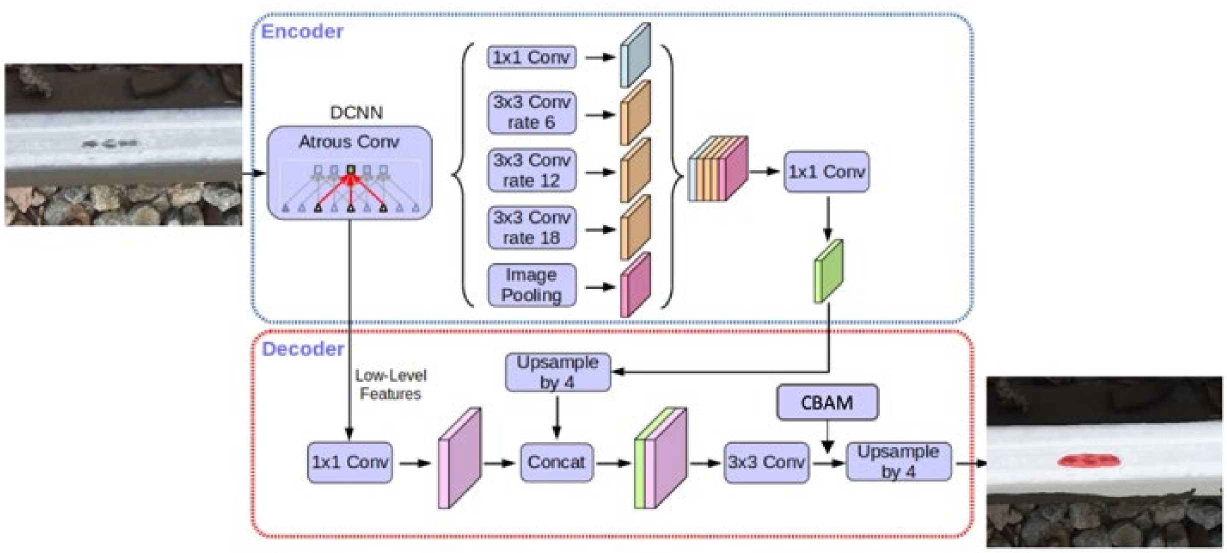

Figure 3: The pipeline of improved Deeplabv3+

In this project, settings were as follows: batch size at 64, learning rate at 0.01, momentum at

0.9, optimizer as SGD, and weight decay at 0.0005. Ultimately, the model achieves the best performance in both evaluation metrics and visualizations. The mean Intersection over Union (mIoU) is the primary indicator of accuracy, with the rail surface class achieving an IoU of 91.77 and an accuracy of 96.36. For defects, the IoU is 63.60 and the accuracy is 81.72. For the trained model, the mean IoU is 84.97 and mean accuracy is 92.60.

5. RESULTS

The trained model was applied to test videos under 8 different conditions, and visualized results were obtained respectively. When the height distance of the UAV from the rail was 3 ft (as depicted in Figure 4), the rail surface was accurately detected whether directly above the rail or 5 ft laterally from the rail. However, rail surface defects were only accurately detected when flying directly above the rails; they could not be detected when 5 ft laterally away from the rails.

At a height distance of 6 ft from the rail (as depicted in Figure 5), the rail surface was accurately detected in both positions. However, while rail surface defects were accurately detected when flying directly above the rails, they were only partly detected when 5 ft laterally away from the rails.

At a height distance of 9 ft from the rail (as depicted in Figure 6), the same detection pattern was observed as at 6 ft: the rail surface was accurately detected in both positions, but defects were only partly detected when 5 ft laterally away.

When the height distance of the UAV was 12 ft from the rail (as depicted in Figure 7), the rail surface was still accurately detected in both positions. Similarly, while defects were accurately detected directly above the rails, detection was only partial when the UAV was 5 ft laterally away.

(a) (b)

Figure 4: Visualized results of RSD_UAV detection: (a) HD = 3ft, LD = 0 ft; (b) HD = 3ft, LD = 5ft.

(a) (b)

Figure 5: Visualized results of RSD_UAV detection: (a) HD = 6ft, LD = 0 ft; (b) HD = 6ft, LD = 5ft.

(a) (b)

Figure 6: Visualized results of RSD_UAV detection: (a) HD = 9ft, LD = 0 ft; (b) HD = 9ft, LD = 5ft.

(a) (b)

Figure 7: Visualized results of RSD_UAV detection: (a) HD = 12ft, LD = 0 ft; (b) HD = 12ft, LD = 5ft.

6. CONCLUSIONS

In this project, a comprehensive UAV-Imagery-base rail surface defect dataset, referred to as the RSD_UAV dataset, was constructed specifically for enhancing the capabilities of rail surface defect (RSD) detection using unmanned aerial vehicles (UAVs).

The improved DeepLab v3+ model was fine-tuned using this customized dataset, resulting in remarkable improvements in defect detection performance, evidenced by a mean Intersection over Union (mIOU) of 84.97 and a mean accuracy (mAccuracy) of 92.60.

Further empirical evaluation demonstrated that the model effectively detects RSD when the UAV is operated between 3 ft and 9 ft above the rail surface. However, as the UAV's altitude increases to 12 ft or more, the detection accuracy diminishes, indicating only partial detection of RSD under these conditions. Additionally, when the UAV is positioned 5 ft laterally from the rail surface, the detection of RSD is significantly compromised at a height of 3 ft, though elevating the UAV slightly improves detection.

Throughout various experimental setups, the rail surface was consistently detectable under all tested conditions, underscoring the robustness of the developed detection system. This research highlights the potential of UAV-based imaging combined with advanced deep learning models for improving the safety and maintenance of railway infrastructure.

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