Railway Track Fault Detection

Project Work

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Abstract

Following project is a continuation of the Mathematic Modeling Practice subject. During the first semester a set of convolutional networks were built to compare on the task of classifying different railway track faults. The project was followed up by contacting MÁV Central Rail And Track Inspection Ltd. who has provided sample dataset for further research and study purposes. This dataset is limited in terms of track failures however it provides the opportunity to apply anomaly detection models. The sample contains video footage of a short section of a single track of approx. 3 minutes, with a few seconds of rail sections covered with grass and/or containing double tracks. The latter two is considered as outlier from the dataset. A set of autoencoder models built to detect these outliers in the sample. The autoencoder is based on the convolutional models of VGG19, ResNet50 and EfficientNetV2L. Different anomaly detection methods were applied, an approach based on the calculation of a loss measure between the input and the output of the autoencoder and IsolationForest algorithm applied on the feature space of the inputs generated by the encoder part.

Acknowledgement

I would like to express my deepest gratitue to my advisor Dr. András Lukács, who supported me with his guidance and valuable insights throughout my project work.

I am also grateful to Mr. Ákos Marosi granting the possibility to have a look into the world of railway track inspection and providing access to the video footages used as dataset. His glowing eyes always represent the deepest passion some can feel towards the railway. I am thankful to Ms. Ágnes Kemény for allowing the joint work taken with the colleagues from MÁV Central Rail And Track Inspection Ltd.

I am also thankful for my partner, friends and coworkers who endured me on this journey while I was balancing on the borders of insanity and obsessesion.

I do hope that the path taken is not the end, but only a beginning.

Contents

1 Introduction

1.1 Previous work

Current research started as part of the studies on the Mathematics Expert in Data Analytics and Machine Learning postgraduate specialization program [1] held by the AI Research Group of Eötvös Loránd University [2]. During the one year program a thesis work has to be created that is often preceeded by a modeling practice in the first semester. This project follows the same approach as railway track fault detection models were already built in the first semester. However the characteristics of the dataset used at that time did not allow a successful application of a model however valuable experience is gained together with a boost of motivation to follow up the topic and deepen the knowledge in the mentioned problem.

1.2 Available results

The work of the first semester can be found at [3]. Following is a short summary of the results obtained.

During the first semester basic convolutional neural networks were built with a classification head to identify images with defective railway tracks. LeNet-5, AlexNet, VGG16 and ResNet50 were applied, partially utilizing transfer learning as well (indicated with *_p in the following Figures).

The dataset was taken from the Kaggle webpage [4] consisting of a limited number of images with defective and non-defective railway tracks. The images combine a high variety of failures with very limited examples leading to a very specific dataset where the provided validation and test split is not representing the initial set of images.

The results of the modeling is shown on Figure 1, where the performance of different bootstrapped models on the splits of the dataset is given.

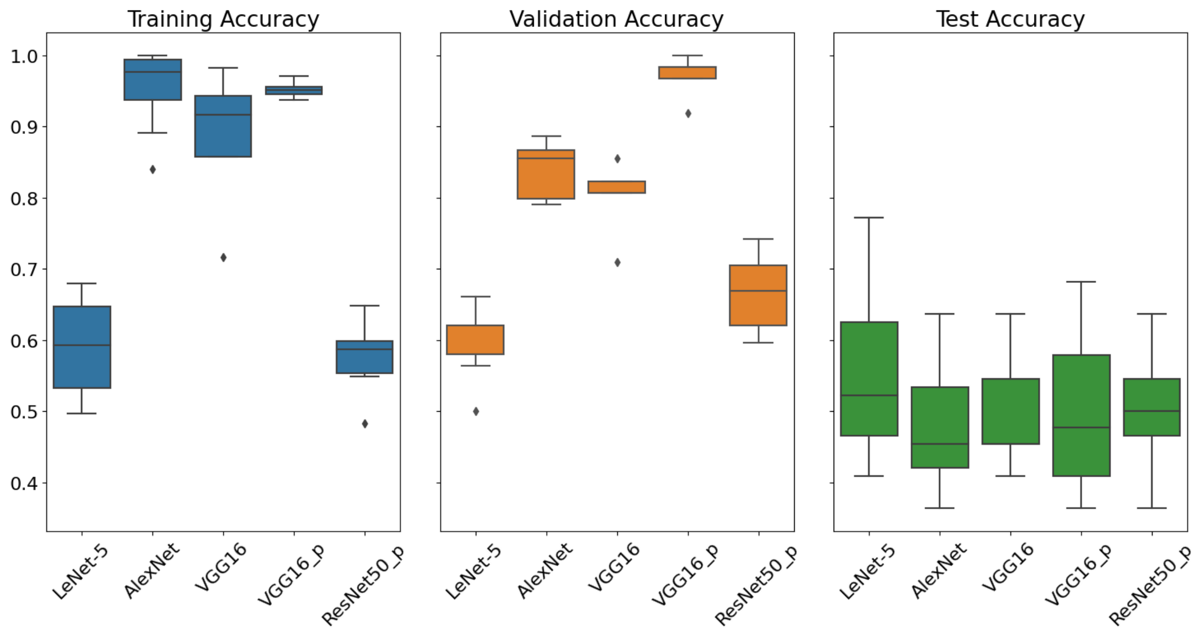

Figure 1: Results of first classification approach on the Kaggle dataset

Most of the models were successfully learned the features of the training and validation datasets, however on the test dataset all failed to classify the images in an acceptable level, mostly achieveing the level of a random classifier only. This lead to the realization that the low number of images compared with the high variety of the track failures will result in a situation where the model can easily learn the specifics of the training and validation dataset preventing of any generalization to the test dataset.

As a followup a search for a more extended dataset and more refined models were started.

1.3 MÁV CRTI Ltd.

The company MÁV Central Rail And Track Inspection Ltd. (MÁV CRTI Ltd.) [5] was approached as they are proficient in railway track inspection and have the equipment and data that could be used for building such classifier model.

The MÁV CRTI Ltd. was established in 1996 by MÁV Hungarian State Railways Co. The scope of the company covers the fields of technical inspection and analysis related ralway tracks, rails and corresponding structures:

- Geometric measurement of tracks and geometric condition survey
- Measurement, examination and qualification of railway rails
- Qualification of new and used superstructure materials
- Examination of bridges
- Examination of substructures
- Development related to rail measurement, examination and line maintenance

A comprehensive overview about the company, it's activities and history can be found at [5] and in [6].

The Rail Diagnostic Department carries out regular measurements on the railway tracks in order to determine the overall condition of the rails and thus ensuring the safety of railway operation. These inspections are carried out by special railway measurment equipment and inspection vehicles, Sstarting from the simplest visual inspections carried out by the maintenance personnel up to special ultrasonic examinations and rail profile measurements. With such equipment rail surface and internal defects can be detected and detailed information about the track profile can be obtained along hundreds of kilometers of railway tracks.

The Rail Diagnostic Department already has some experience with machine learning based rail defect detection providing options for benchmarking the models created through this project. It also reflect the importance of such approach, as today visual inspection demands heavy efforts let that be the work done by the maintenance personnal (intrinsically walking along the tracks) or the monitoring of the video footages taken during the inspection rides.

Currently MÁV CRTI Ltd. operates two vehicles for rail inspection purposes, the SDS and FMK-008 shown on Figure 2, both equipped with different measurement and inspection systems. Fortunately both of them is equipped with video recording, however with different systems. After a first view on the video files the system of the SDS vehicle is selected for a first modelling approach.

SDS

FMK-008

Figure 2: Railway inspection vehicles of MÁV CRTI Ltd.

1.4 Modeling approach and problem statement

During the first part of the project convolutional neural networks with classification head were applied on annotated dataset. A step forward was taken by obtaining real world data, however this comes with the burden of missing labeling. Therefore the modeling approach was also changed from supervised learning to unsupervised learning. In this way the problem was reformulated and traced back to anomaly detection, thus resulting in the following key questions:

Q1 Can anomaly detection algorithms used to detect rail defects?

Q2 What models could be applied on the given dataset?

Q3 What accuracy rate can be achieved with the models?

1.5 Structure of the document

The Section 2 gives a deep view on the sample dataset. The structure of the models introduced in Section 3. The realization of the models, structure of the software code is explained in Section 4. The results are interpreted in Section 5 and discussed in Section 6. Further steps and possible improvement options covered with a summary of the results in 7.

2 The dataset

The video system of the SDS vehicle records both rails from two angles resulting in four video footages parallel. A single footage was selected as it provides a static positioning relative to the tracks with good protection against changes of the lightning of the surroundings. The video system records with a resolution of 720x288 (width x height) with RGB channels at 50 fps rate. Some examples of the images extracted from the video is shown on Figure 3.

A single footage sample video of approximately 3 minutes was provided as a starting point. This video contains a side view of a rail, that is defined as *normal* rail along with a few seconds of rail covered with grass of showing a double rail section.

Normal rail Normal rail Normal rail

Rails covered with grass Double rails

Figure 3: Sample images from the dataset

This sample video was sliced to images, resulting in the dataset shown in Table 1. The resulting dataset is imbalanced, and the so-called outliers can be easily identified. In general annotation can not be assumed for such problems, however in this case it was provided manually to grant performance evaluation possibility.

Image type	Number of images
Normal rail	8640
Rail covered with grass	64
Double rails	29
Total	8733

Table 1: Dataset obtained from sample video

There is no slurring observed on the images that is remarkable considering that the video is taken with a vehicle speed up to 80 to 100 kilometer per hour. However a slight fisheye distortion can be seen that is noticeable mostly in the rail itself, as it is not tend to follow a stright line, a small bending effect is given. Also the lighting of the pictures result in a brighter spot on the center. The image quality remains stable in the sample video, including the illuminance that is secured by the shrouds applied on the vehicle around the cameras.

During modeling besides augmentation no image manipulations were applied except the normalization during entering the neural network.

Later on the course of the work MÁV CRTI Ltd. provided further videos from both vehicles ranging up to 450 GB of raw data that can be used for further training, evaluating or tuning the models.

3 Description of the model

3.1 Autoencoders

Autoencoders are widely used in Deep Learning applications with the main intention the describe a set of data, mostly targeting dimensionality reduction of creating a general represenation of the dataset. This allows the application of such models for anomaly detection, that can be translated as outlier detection problem in this generated representation, called feature vector or latent space. Such approach does not require annotated dataset, therefore belongs to the class of unsupervised learning algorithms.

The general structure of Autoencoders are shown in Figure 4.

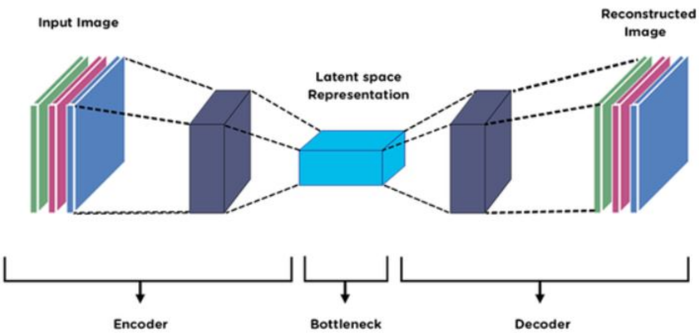

Figure 4: General structure of Autoencoders [7]

A comprehensive overview about Deep Learning methodology is given in [8]. Chapter 14 of this book explains that mathemathical structure of Autoencoders. Another introduction can be found at [9].

3.2 Type of Encoders

3.3 Applied Decoder

3.4 Basis of anomaly detection

3.5 Model training

3.6 Performance evaluation

4 Software implementation

5 Results

6 Discussion

7 Conclusion

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References

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