

Railway Track Fault Detection

Project Work

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Spring Semester 2022/2023

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 gratitude to my advisor Dr. András Lukács, who supported me with his guidance and valuable insights throughout my project work. Also I would like say thank you to the colleagues of AI Research Group of Eötvös Lóránd University who provided the possibility to attend on this special one-year training and gave their best to enlighten us as students to the world of data analytics and data science, Machine Learning and Artificial Intelligence.

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 obsession.

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

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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 preceded 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.

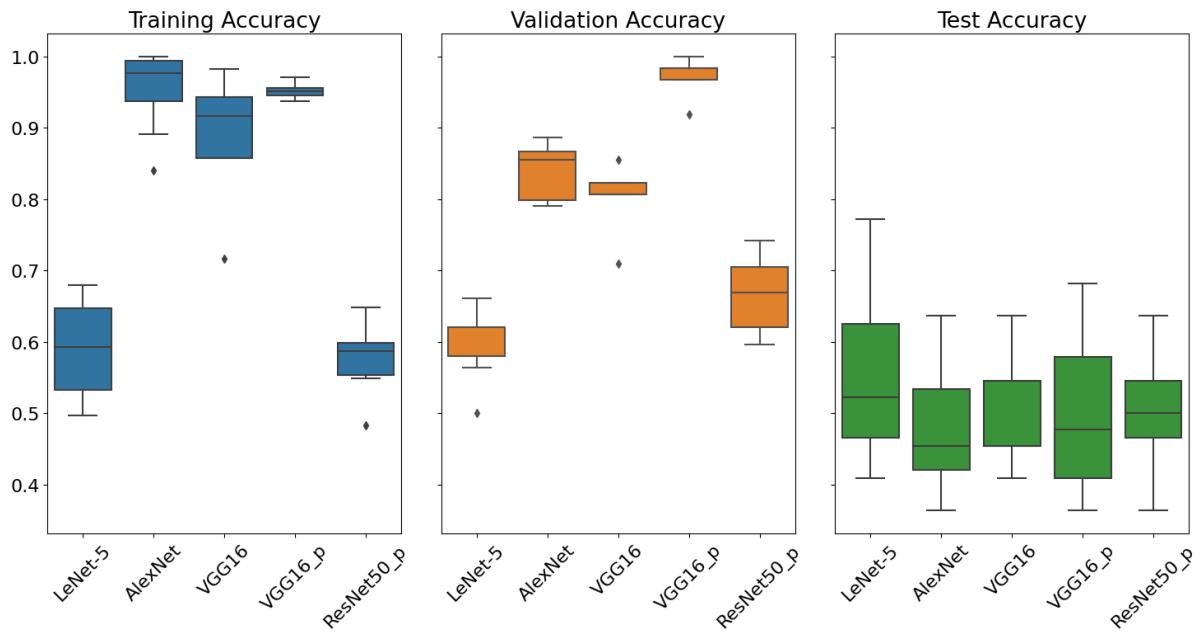


Figure 1: Results of first classification approach on the Kaggle dataset

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 achieving 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 railway 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 measurement equipment and inspection vehicles, starting 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 personnel (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.

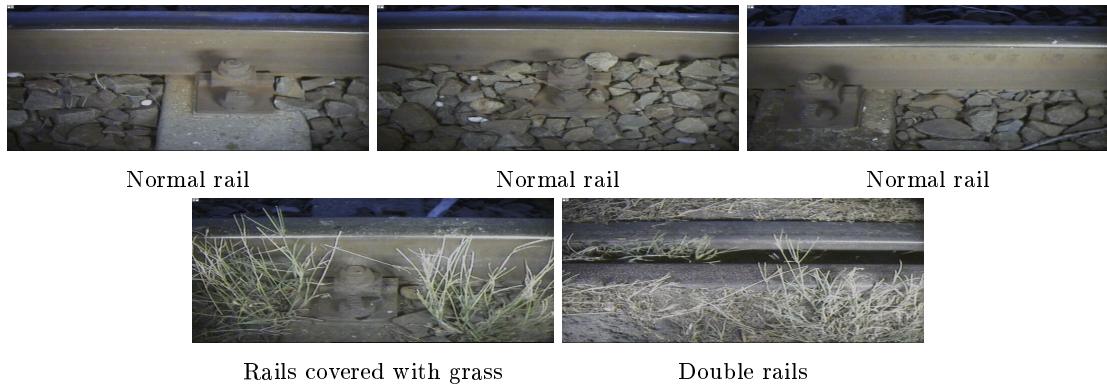


Figure 3: Sample images from the dataset

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 straight 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 and resizing to 704 x 288 x 3 to ensure decoding of the images to the same original size (please see Section 3).

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 to describe a set of data, mostly targeting dimensionality reduction of creating a general representation 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.

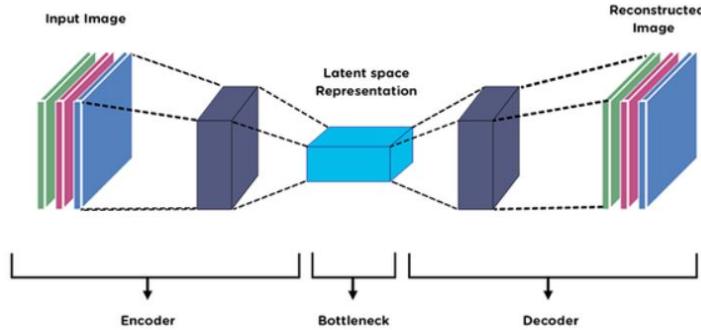


Figure 4: General structure of Autoencoders [7]

The basic idea behind an Autoencoder model is to generate feature vectors from the input dataset (encode the dataset), this is the so-called Encoder part. This set of feature vectors, called as latent space contains the representation of the dataset. In the second part, the Decoder part tries to recreate the input data based on the feature vector generated by the Encoder. In current use case this means that the single images of the rail is translated to feature vectors and then the original image is recreated with some error using the Decoder.

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

3.2 Type of Encoders

During the research four type of Encoders used as listed below.

- VGG19 with and without batch normalization
- ResNet50
- EfficientNetV2L

The VGG19 is one of the first deep convolutional networks introduced in [10]. In the second model batch normalization was added after each convolutional layer. The ResNet50 [11] overcomes the issue of the vanishing gradient by adding the skip connections. EfficientNetV2 [12] is developed to reduce training time and provide better parameter efficiency than previous models.

During the encoding the input image sizes are gradually reduced in four steps, resulting different shapes of the latent space due to the different number of filters applied. An overview of the resulting latent space considering an input size of 704 x 288 is shown in Table 2. For comparison the original image of size 720 x 288 x 3 has a total number of 622080 to describe a single instance.

Encoder type	Width x Height x Filters	Number of parameters
VGG19	22 x 9 x 512	101376
VGG19 with batch normalization	22 x 9 x 512	101376
Resnet50	22 x 9 x 2048	405504
EfficientNetV2L	22 x 9 x 1280	253440

Table 2: Latent space shape of different Encoders

3.3 Applied Decoder

Once the feature vectors obtained, the original image can be reconstructed. In current study VGG19 is used as basis decoder model. As the processing of the data has to be done backwards, the whole structure is reversed and the convolutional layers are replaced with transposed convolution.

In order to fit the Decoder input to the Encoder output a FilterMatching part is introduced. As the difference between the latent space is only the number of filters, the shape is adjusted via additional convolutional layers:

- In case of the VGG models, an identity mapping is applied
- For the ResNet50, a two step approach is followed, each is halving the number of filters
- When applying the EfficientNetV2L model, also a two-step decomposition is introduced first the number of filters is reduced to 896 and then to 512.

3.4 Basis of anomaly detection

The main question of anomaly detection is how far can we distinguish between *normal* and *abnormal* data vector, that is in this case an image or a feature representation. There are several approaches (a short list can be found at [13]), among those we applied the replication neural network, more in particular an Autoencoder approach. This brings us to two main approaches that we followed.

The first one is to use the decoding capability of the network and define the outliers of the dataset by the calculated loss. The assumption behind is that during training the model can learn and generalize to the input images that are *normal*, but can not learn the few outliers, therefore the calculated loss shall be higher in latter case as the *abnormal* part of the image can not be recreated so well. The definition of the loss (or distance between original and replicated image) plays an important role in the detection.

In current approach the loss function is set as the pixelwise mean squared error of the input and the decoded image. The threshold to designate an image as outlier is to have higher loss value (distance between input and output image) than the mean loss overall the whole dataset and three times the standard deviation added together.

The second approach that we utilize the representation of the images and trace back the outlier detection to the latent space. The representation created by the encoder shall bear all the key characteristics of the images, if an image contains a certain defect (and thus becomes an outlier), then its representation shall be an outlier as well. This method allows to introduce several tools for detecting the outlier vector, such as Isolation Forest or any basic clustering methods (DBSCAN, OPTICS, etc.).

Our research focused on the Isolation Forest, that was applied on the latent space with default settings.

3.5 Model training

Transfer learning is applied in case of the Encoders to ensure an efficient approach, the model weights from the Imagenet pretraining is selected for this purpose. In case of the Decoders no transfer learning is available due to the reversed structure of the network, there only a random initialization was used.

The loss function is defined as pixelwise mean squared loss between the original and replicated images. Adam optimizer is applied with a learning rate of $5 \cdot 10^{-6}$. The batch size for training is set to 8.

The dataset is splitted to *train*, *validation* and *test* set, considering the imbalance nature of the dataset, during split a stratified approach was applied. The training of the models were done on the *train* dataset for 100 epochs, the *validation* set was used to monitor how well the model generalizes and to detect possible overfitting or other training issues. The *test* dataset was used for independent analysis of the model, how the results presented in Section 5 is interpreted over the whole dataset offering the

opportunity to compare which images detected as outliers (or missed) by the different detectors models (loss based or Isolation Forest).

3.6 Performance evaluation

The first approach on the performance evaluation is the general classification metrics based on the confusion matrices of each approach. Furthermore a visualisation is provided via a two step dimensionality reduction approach: first a PCA was used to determine the 50 most important features of the dataset, then a t-SNE was applied to find the two most important feature. This allows a graph representation of the dataset. This approach was applied on the input images, latent space vectors, filter matched vectors and on the decoded images. This allow a visualisation how outliers behave over the whole model.

4 Software implementation

The project is written in Python language partially in python scripts directly, partially in Jupyter notebooks. The documentation is created in L^AT_EX. The overall software code is stored at https://github.com/demustamas/project_work. Due to storage limitations the trained model files and the original dataset is not uploaded to GitHub. The basic folder and file structure is as follows:

1. `./build` - Build directory of L^AT_EX, contains project documentation
2. `./data` - Contains the dataset (not available on GitHub)
3. `./results` - Contains resulting models, images, tables
4. `./tex_content` - L^AT_EXdocumentation files
5. `./tex_images` - L^AT_EXimages for documentation
6. `./tex_refs` - Style files, bibliography
7. `./toolkit` - Contains main scripts
8. `./toolkit/classes.py` - Class definitions for loading the dataset
9. `./toolkit/pytorch_tools.py` - Class definitions for Pytorch
10. `./project_work.ipynb` - Jupyter notebook project file
11. `./project_work.tex` - Main L^AT_EXdocumentation file
12. `./project_work_pres.tex` - Final presentation of the project
13. `./video_slicer.ipynb` - Jupyter notebook used for slicing the videos to images

The raw video files (binary files) were sliced using the `video_slicer.ipynb`. The anomaly detection is then performed by `project_work.ipynb` and the results, including trained models, extracted plot images, csv files are stored in `./results`.

The documentation is created in L^AT_EX, the main file is `project_work.tex`, a final presentation will be stored under `project_work_pres.tex`.

The main script files are `classes.py` and `pytorch_tools.py`. These contain the class definitions used to import the dataset, define the models of the Autoencoder and AnomalyDetector with the corresponding methods used for training, predicting and evaluating the results.

The scripts are prepared to run either on CPU or on GPU, depending on the available IT infrastructure. The computation expensive steps were run on the servers of AI Research Group of Eötvös Lóránd University.

5 Results

5.1 Encoding via VGG19

The learning curves of the Autoencoder training is presented on Figure 5. The initial high loss values are reduced significantly during the first few epochs. The train and validation losses converge quite close to each other due to the fact that the train dataset (as the overall dataset itself) contains mostly *normal* rail images. Also the variation of the curves are very small, the validation set represents well the training set. The validation curve is slightly above the train losses, there is no sign of overfitting or abnormal training of the model.

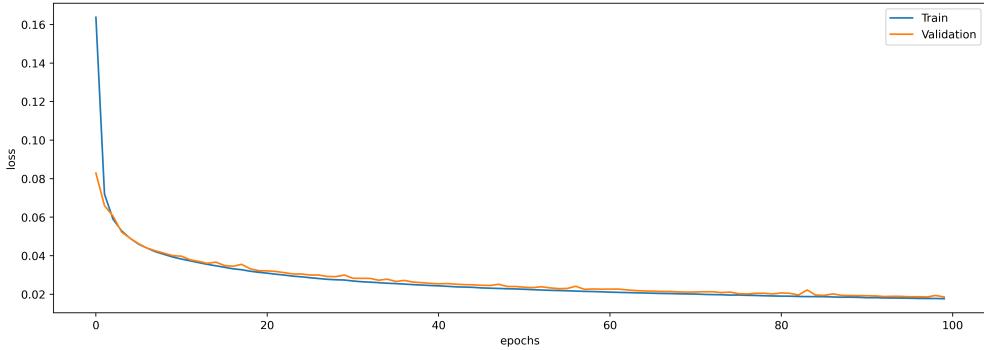


Figure 5: Learning curve of the VGG19 Encoder

After training some example images are predicted (encoded and decoded) to visualise the performance of the Autoencoder. This is represented on Figure 6. The sample autoencoded images show the main characteristics that is recorded by the model. The vertical shiny edge of the rail is easily identified along with the side surface. The details that are close to the center of the image or are brighter parts of the image are more likely to be captured. Even the ballast stones can be recognized demonstrating the power behind such models. It is to be noted that the reproduced image is not fully complete, the more towards the image edge, the more black areas given resulting in high loss of information.

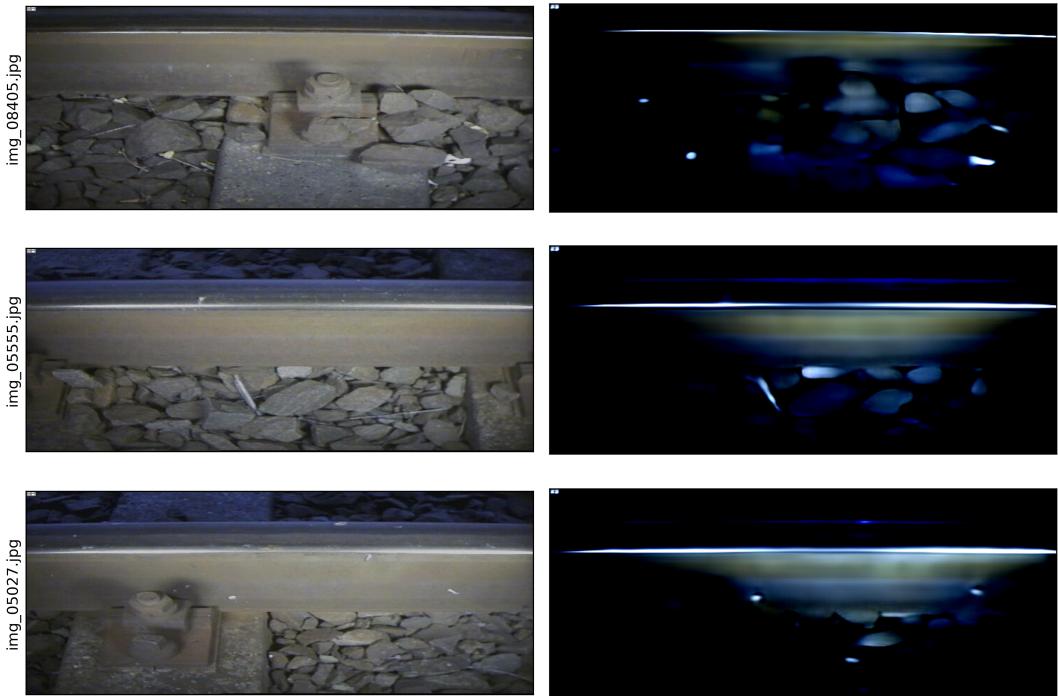


Figure 6: Predicted images in case of VGG19 Encoder

The visualization of the different model stages based on the PCA / t-SNE approach is depicted on Figure 7. The colors indicate whether we observe a *normal*, *grass covered* or *double rail* image, the latter two is considered as outlier. The alpha value of the markers indicate the loss value of the image, the higher the alpha the less transparent the marker is. The outlier images form a certain clustering already among the input images, that is, at least to some extent, retained after encoding. This can be seen on the input phase already in the top right and center bottom part. These clusters are separated partially after encoding. There is a clear cluster made of outliers after encoding in the bottom right part, but this cluster does not contain all members, some are still embedded among the *normal* images, in the top right part, however slightly moved to the boundary of it. It can be also seen that after decoding these outliers are structured back to their original position in the visualization space. This indicates that the encoding is somehow clustering the dataset, whilst the decoding part readjusts this clustering back to its origin, basically proving that the main idea of the Autoencoders is represented in the model.

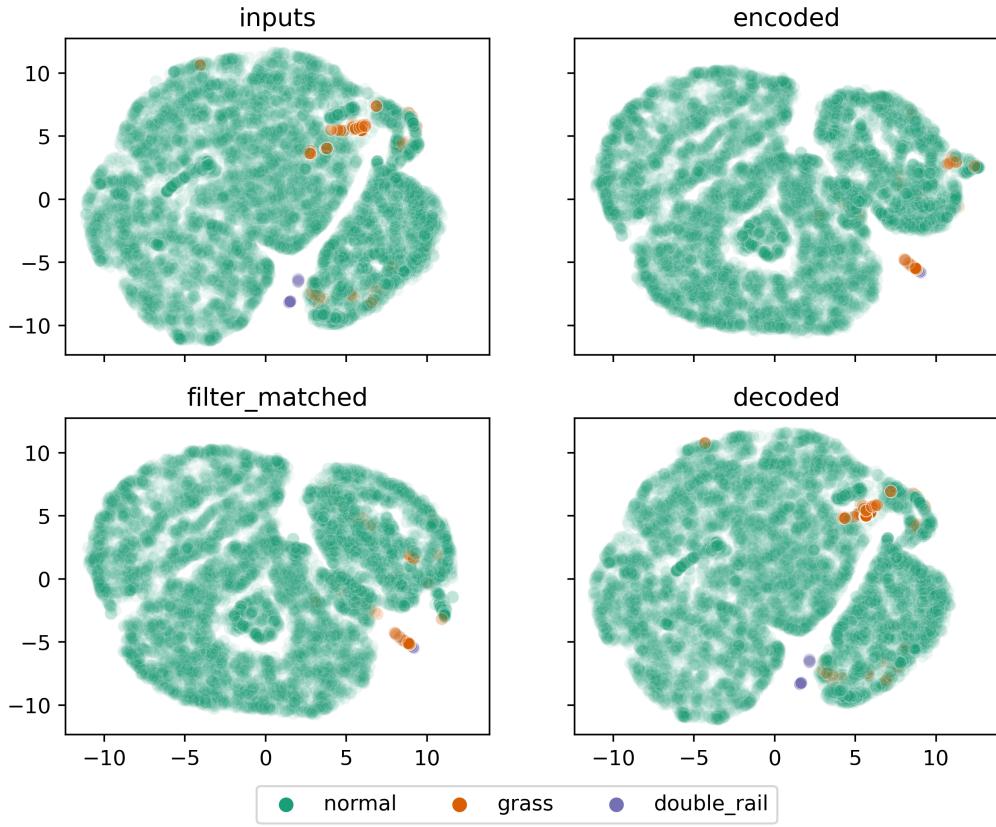


Figure 7: PCA / t-SNE visualization of the VGG19 Encoder

The loss values of each image of the whole dataset together with a marking of the outliers is shown on Figure 8. The peaks in the loss value are remarkably indicating the positions of the outlier images. The concentration of the outliers are also confirmed based on the video footage, first a few seconds of grass covered section can be seen, then in the second part a longer period of grass coverage with the appearance of the double rails is present in the video. It is to be noted that, for example in case of the first *grass* image the loss value is not so well distinguishes the image from its neighbouring images. Similarly, but in the opposite direction, at some *normal* pictures the loss value is significantly higher than the values of the preceding or following images. This denotes that this approach most likely will not a perfect identification of the anomalies.

The confusion matrices for the loss-based and Isolation Forest anomaly detection techniques can be seen on Figure 9. The loss-based approach identifies the % of the outliers correctly, whilst providing no false positive. The threshold of three times the standard deviations seems to be a quite conservative approach, considering the actual use case that the target is to identify all the outliers, even with the cost of increasing the false positive rate, lowering this threshold might be useful. The Isolation Forest gives slightly different results, finding approximately half of the outliers, and providing some number of false positives.

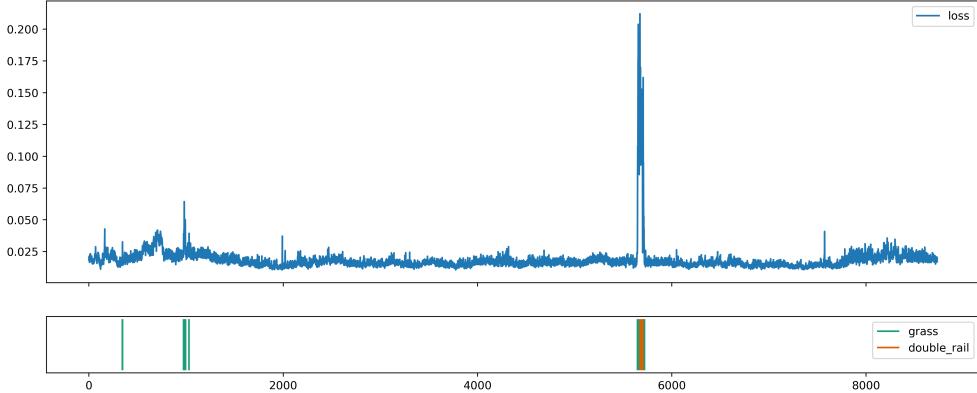


Figure 8: Loss values of the dataset with VGG19 encoding

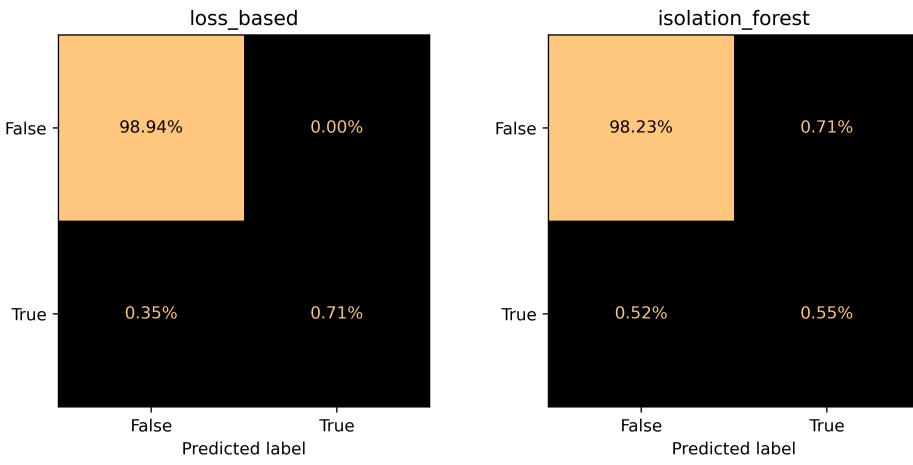


Figure 9: Confusion Matrices of the VGG19 Encoder

5.2 Encoding via VGG19 with batch normalization

The batch normalization did not deliver a significant change to the characteristics of the learning curves as can be seen on Figure 10. Similar observations can be done as for the model without batch normalization. After the first few epochs the loss values significantly decrease and continues getting reduced indicating that the model is capable to learn new features. The train and validation losses run quite close to each other due to the many very similar images, and indicating a good representation capability of the train dataset. No overfitting or training issues can be seen, however the validation loss curve seem to show slightly higher variance. At 100 epoch the loss value is slightly higher than it was with the VGG19 model. The difference is minor, normally the batch normalization shall decrease the learning times of a model, however the resulting loss values highly depend on the weight initialization as well. In this case the initial validation loss was also higher at start compared to the pure VGG19 model (0.099 vs 0.082, with and without batch normalization respectively).

The samples of the predicted images bear the same characteristics as it was seen on the VGG19 model. Some examples are given on Figure 11. More details are reconstructed in the center of the picture or in brighter part of the image. As basic feature, the main edge of the rail is also visible together with the side surface. Smaller details such as outlines of ballast rocks are also captured to a certain extent. This shows that the introduction of batch normalization did not change significantly the quality of the decoded pictures. However still not recreating the whole image.

A more interesting change can be identified on the PCA / t-SNE visualization on the Figure 12. The change of the cluster follows the same character as without batch normalization, but the separation of the outliers happens in a different way. The outliers that were still part of the *normal* cluster, close to the boundary, now show a more accented deviation based on their loss values as can be seen on the top right part of the encoded phase. But some outliers are stucked deeper inside the clusters of the *normal* images. This can be seen on the bottom left part of the encoded phase. The outliers on the bottom right part are still well isolated from the main *normal* cluster. During reconstruction of the images, the decoded visualisation shows a clear difference to the input characteristics based on the position of the outlier images. As the PCA and the t-SNE and their joint effect is

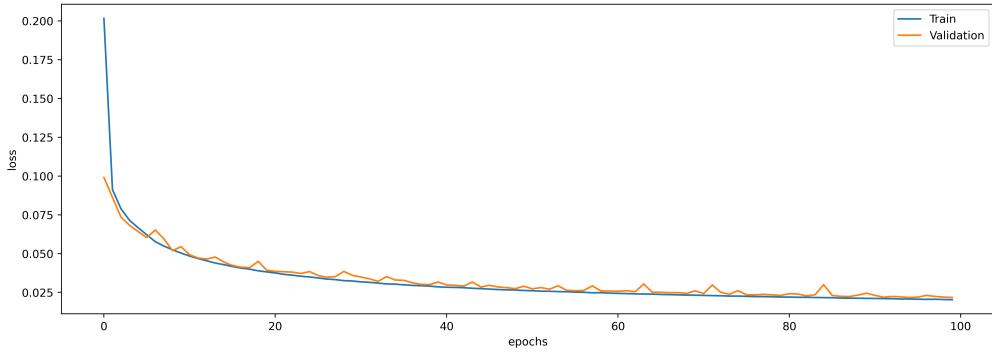


Figure 10: Learning curve of the VGG19 (BN) Encoder

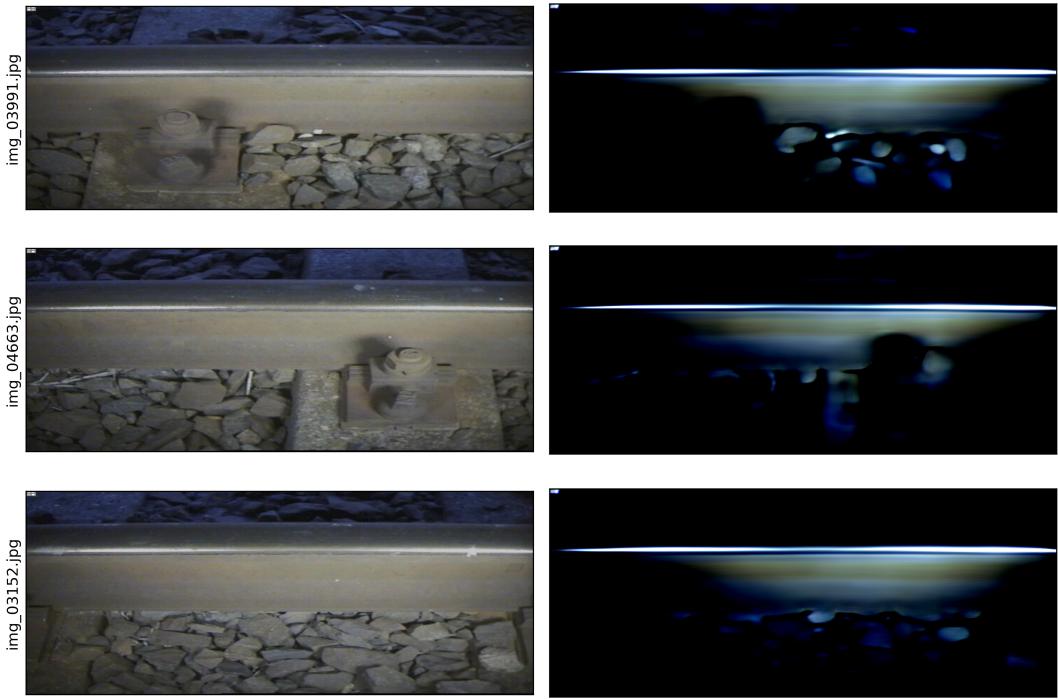


Figure 11: Predicted images in case of VGG19 (BN) Encoder

not optimised, it can not be excluded that this change is resulting only from the visualisation technique, however we shall keep in mind, that this could be also an indication of a different model behavior.

The loss values of the images show a very comparable series as the VGG19 model as shown on Figure 13. Emphasizing that the effect of the batch normalization can not be really identified through the comparison of the loss values. Most of the outliers are indicated with high loss values, especially the part with the *double rail* cluster. On the other hand some outliers still *hide* inside the loss values as it is not deviating from the others. An example for this is the first *grass* outlier.

Interestingly the confusion matrices deliver different results than without batch normalization. These matrices are shown on Figure 14. The loss-based approach delivers almost exactly the same results, there is a slight change that can be captured in the increase of the true positive indications and thus on the reduction on the false positives (missed outliers). Applying the Isolation Forest algorithm on the bottleneck vectors shows a slight performance increase, the true positive predictions increased, whilst the false positive and true negative rate is reduced. This reduction is significant in case of the true negative indications.

5.3 Encoding via ResNet50

The learning curves as shown in Figure 15 act in a very similar manner as with the VGG19 models, the difference that can be identified is the variation of the validation losses over the epochs. Apart from that, the same starting and resulting loss is reached by the model, without any overfitting or training problems. The

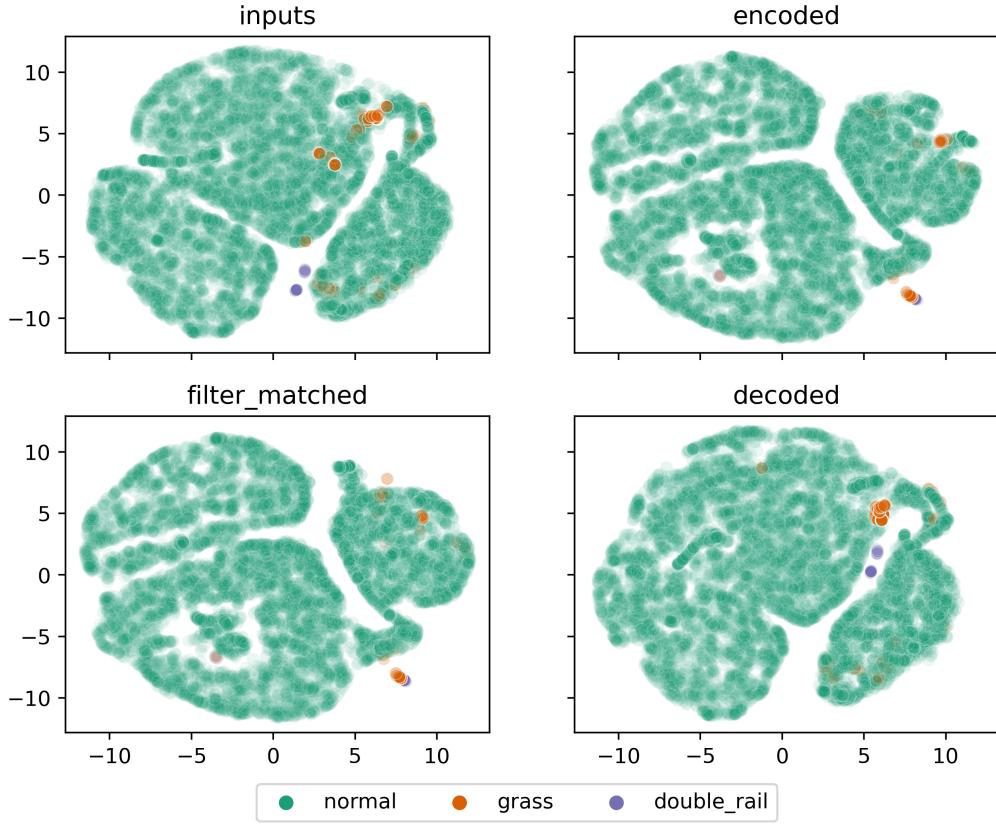


Figure 12: PCA / t-SNE visualization of the VGG19 (BN) Encoder

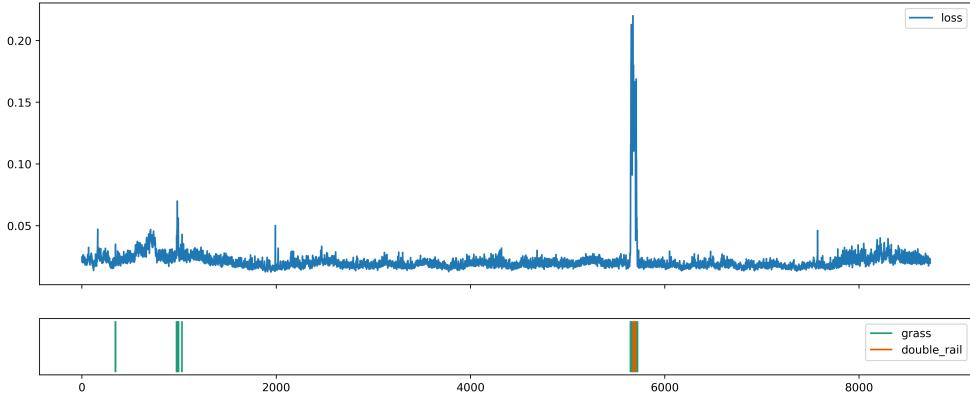


Figure 13: Loss values of the dataset with VGG19 (BN) encoding

validation curve follows the training curve, supporting that the training dataset is representative to the whole dataset. It is to be noted that the training was done in different dataset split ups for all models.

The autoencoded images follow the same pattern as before, major features of the rail is regenerated, the details are concentrating to the center or brighter parts of the images, the main edge of the running surface of the rail and the side surface both can be identified. The representation of the ballast rocks also present. These are presented on Figure 16. It can be concluded that the model learnt to encode the images to feature vectors and then the decoding is also successful, however it has to be noted that the resulting image is far from complete.

The PCA / t-SNE visualisation shows a little enhancement in the behaviour of the model on Figure 17. The outliers of the input images are encoded in a way that they tend to separate from the major *normal* cluster, even the ones that remained in this cluster are closer to the boundary as shown on the top right part of the encoded subfigure. Even it can be seen that this region or the boundary is *opening up* and the *normal* images do not encompass these outliers so much. The bottom right concentration of the outliers are separating clearly with this model, as seen with the other models as well. The decoded images retain the clustering in a strict manner,

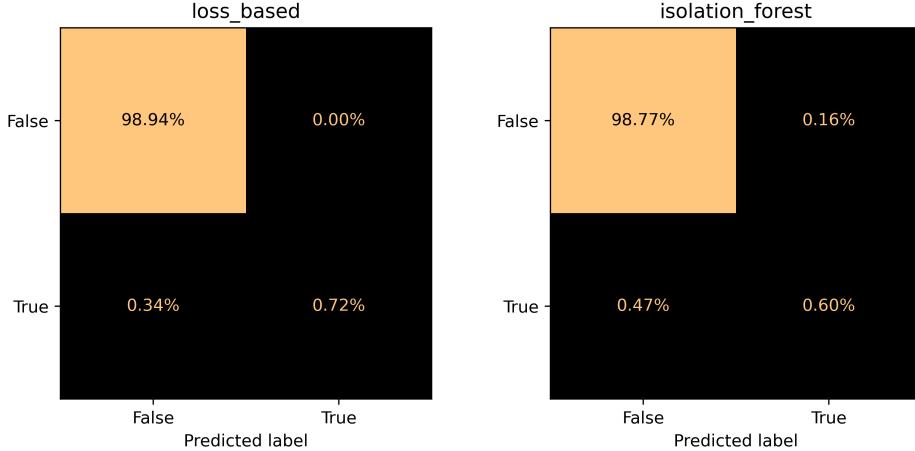


Figure 14: Confusion Matrices of the VGG19 (BN) Encoder

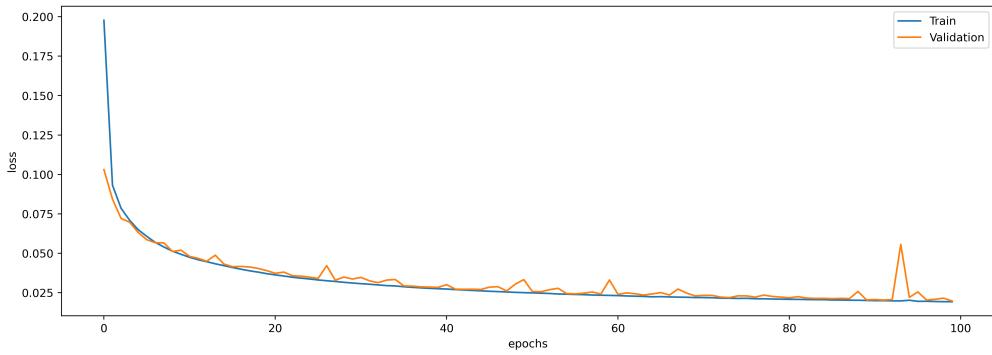


Figure 15: Learning curve of the ResNet50 Encoder

compared to the distribution of the outliers on the input visualization, the decoded outliers form a more closed cluster. Some of the outliers (that usually have low loss values compared to the other anomalies) still remain inside the *normal* cluster through the whole model.

The loss values depict the same variation over the images as seen for the VGG models, depicted on Figure 18. The majority of the outliers can be easily identified, although not all of them have a high loss value and some images with high loss values belong to the *normal* rail class. The loss values do not indicate a difference between the models seen so far.

The classification metrics stay between the VGG19 models with and without batch normalization. The confusion matrices can be seen on Figure 19. The loss-based approach delivers the same performance as the threshold still too conservative, approximately $\frac{2}{3}$ of the true positives identified correctly. The Isolation Forest algorithm identifies true positives in higher rate than the VGG19 without batch normalization, however the false positives remains on the level of a prue VGG19 model.

5.4 Encoding via EfficientNetV2L

Observing Figure 20, the learning curves of the EfficientNetV2L model, there is a change in the patterns seen among the other models. The curves are comparable in terms of general characteristics, the starting and resulting losses are comparable and the majority is reduced in the first few epochs. In detail however the variance of the validation losses do not show a further increase, it steadily follows the training curve. Also for this model there is no overfitting or any training issue detected, the training data seem to represent the whole dataset, this is supported by the validation curve.

The predicted images are similar to the ones seen before, the basic features are well grabbed and the details are focusing around the center or bright part of the images. The rail itself and ballast stones can be easily recognised, the model (same as for the other models) captures the edges easily. The reconstructed images however still not deliver full pictures, loss of information due to incompleteness is assumed. The sample images are presented on Figure 21.

Reducing the dimensions to a plane results comparable characteristic behaviour as the other models as shown

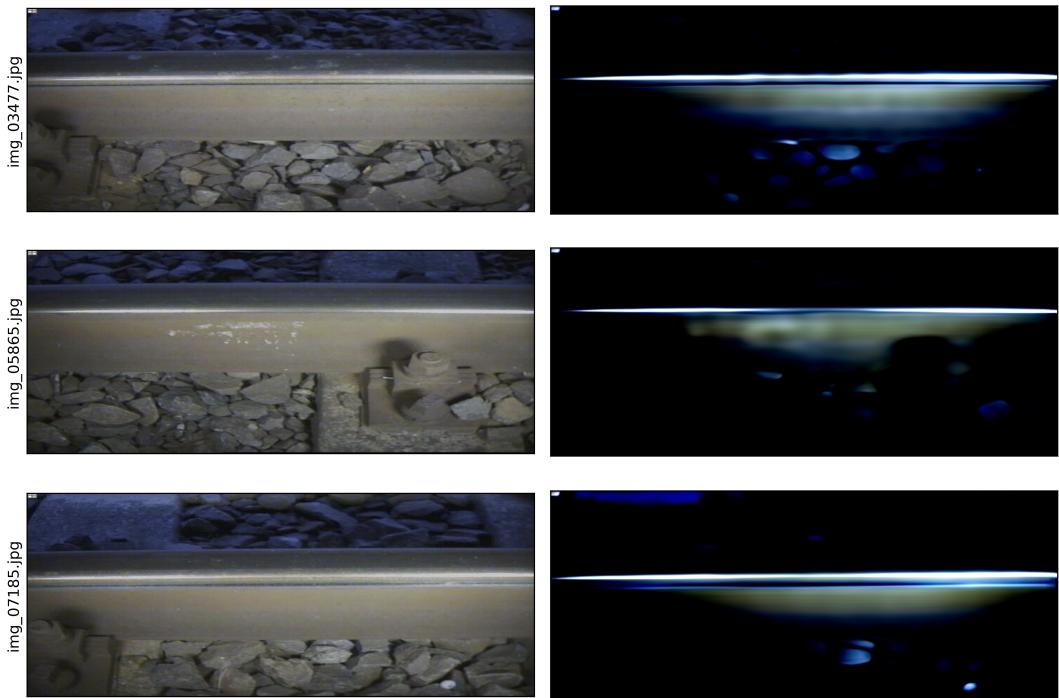


Figure 16: Predicted images in case of ResNet50 Encoder

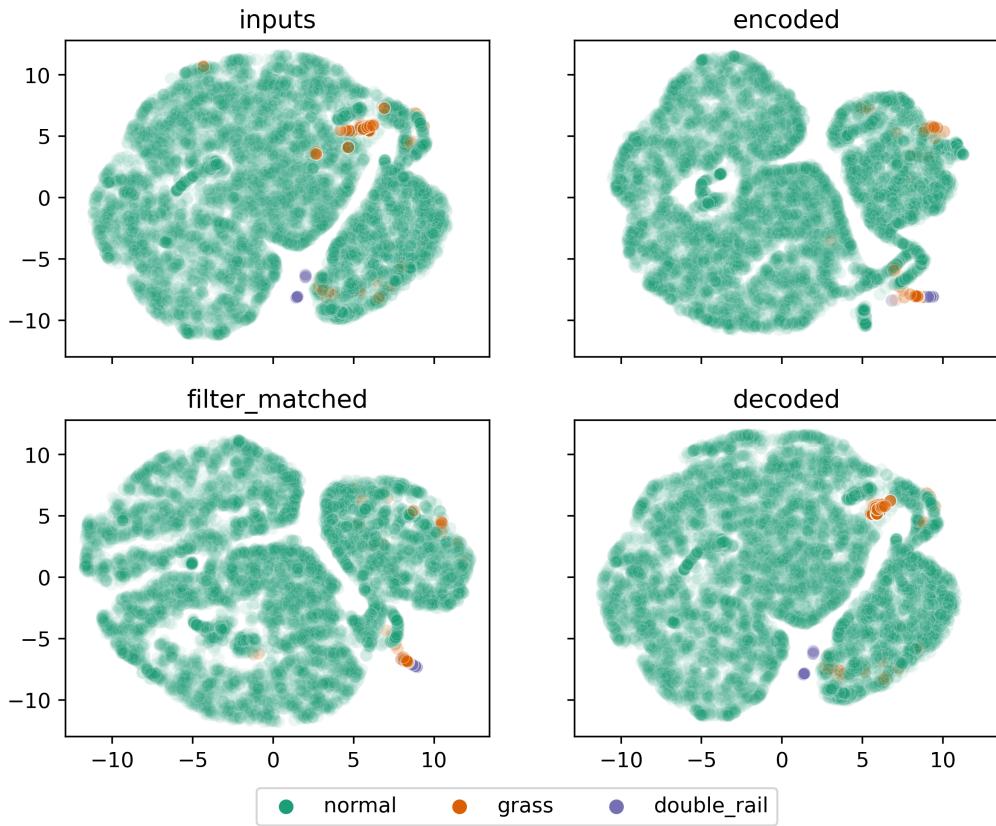


Figure 17: PCA / t-SNE visualization of the ResNet50 Encoder

on Figure 22. Although there are some differences that need to be noted. First, the outliers are captured and separated from the *normal* cluster, especially on the bottom right part of the encoded view, however the separation is not as clear as was for example in case of the ResNet50 Encoder. Secondly the outliers that are

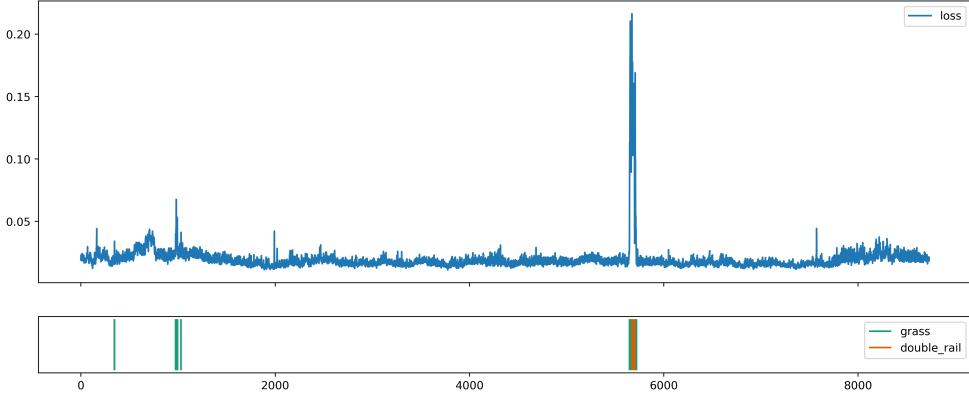


Figure 18: Loss values of the dataset with ResNet50 encoding

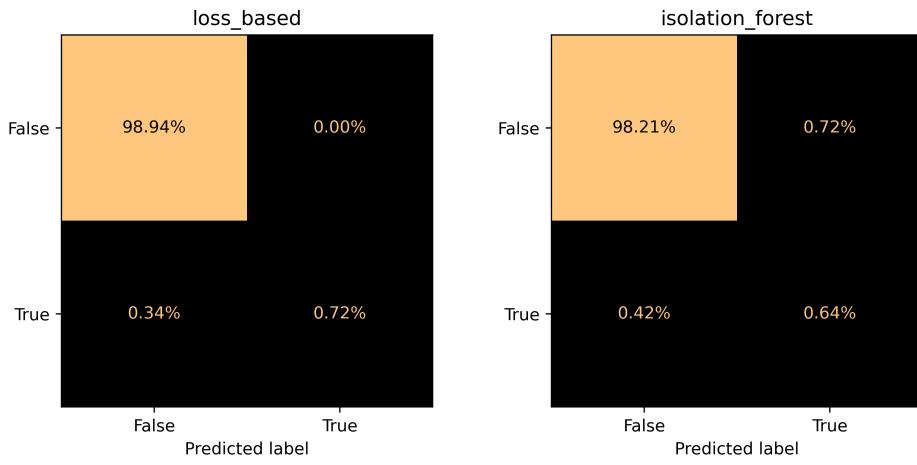


Figure 19: Confusion Matrices of the ResNet50 Encoder

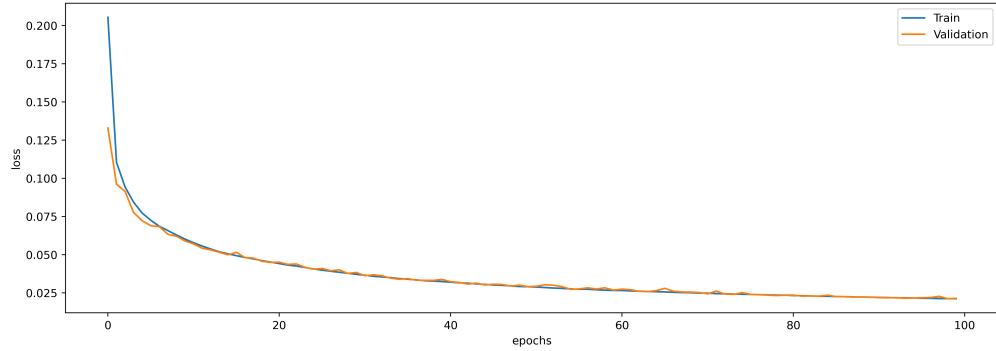


Figure 20: Learning curve of the EfficientNetV2L Encoder

stucked on the top right part of the encoded view inside the *normal* cluster are now moved more to the boundary and even the *normal* cluster is opened up better. After decoding back the images, the resulting feature plane shows that the outliers are placed back more concentrated to their original place indicating a certain loss of information and generalization of the model.

The loss values of the full dataset is shown on Figure 23. Once again the same characteristics can be seen as for the other models. The loss metric alone is not necessarily indicates the performance of these anomaly detectors. Most of the outliers can be found by comparing the loss values with a given threshold, however some of those remain embedded and can not be retained with this method.

The classification metrics as shown with the confusion matrices on Figure 24 present a similar performance of the loss-based approach, a little bit more than $\frac{1}{3}$ of the outliers found. The Isolation Forest delivers one of

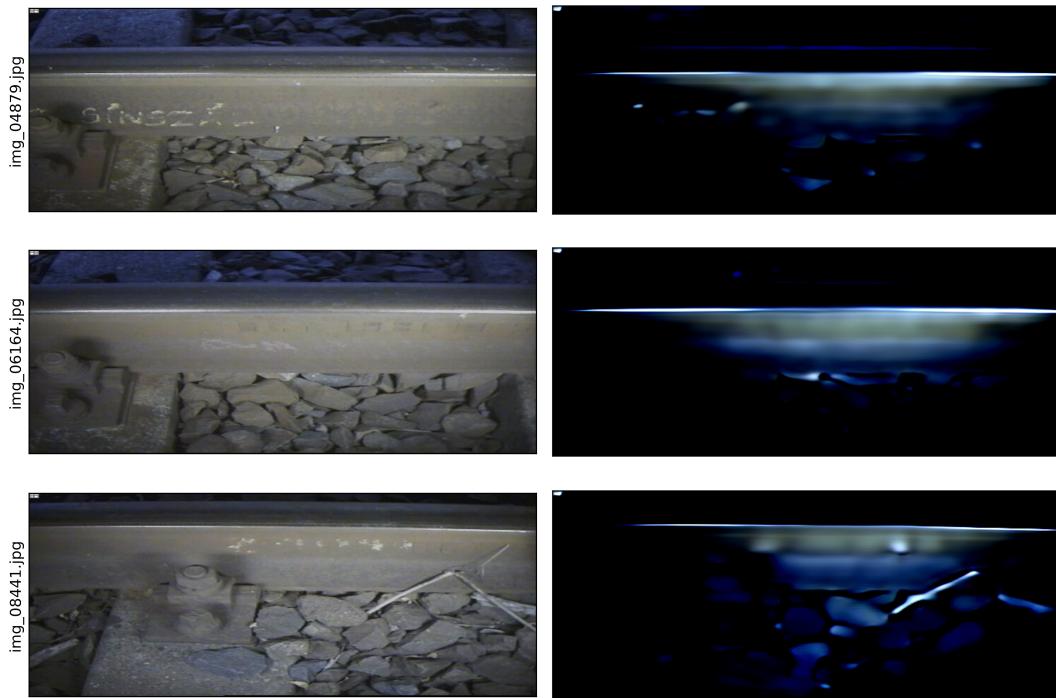


Figure 21: Predicted images in case of EfficientNetV2L Encoder

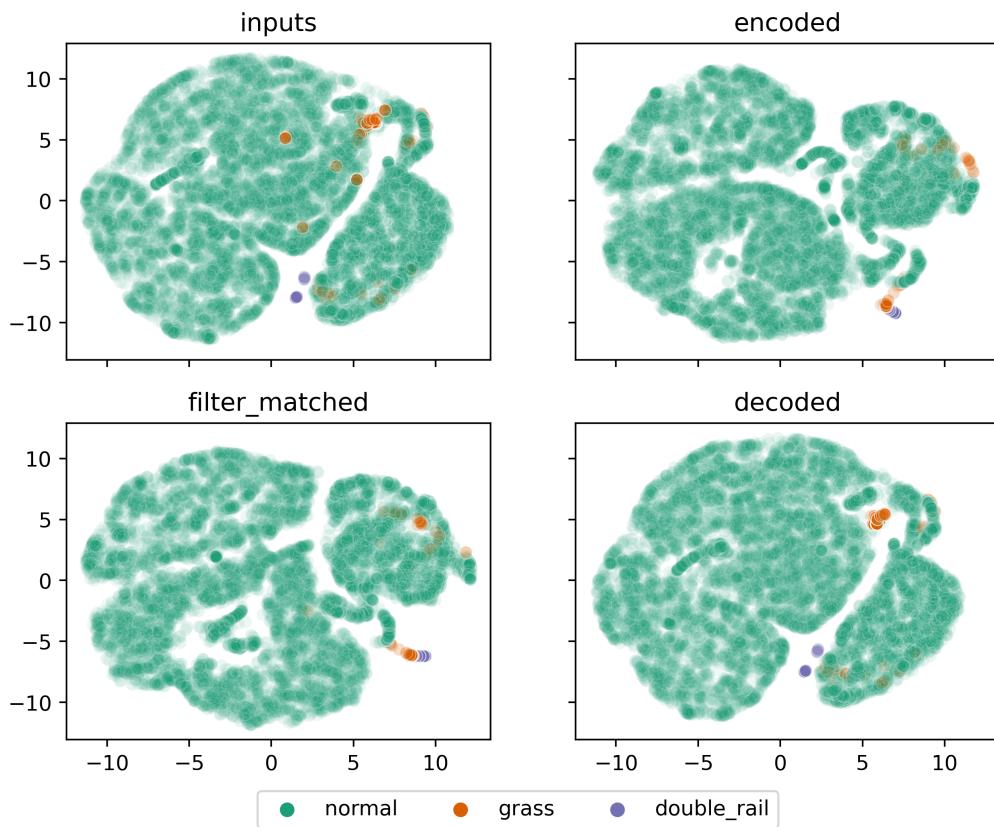


Figure 22: PCA / t-SNE visualization of the EfficientNetV2L Encoder

the best true positive indications, but on the cost of worst false negative rate.

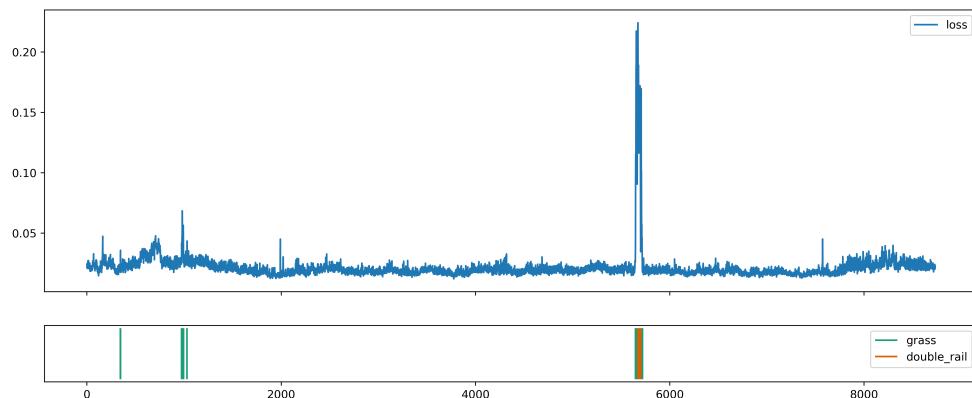


Figure 23: Loss values of the dataset with EfficientNetV2L encoding

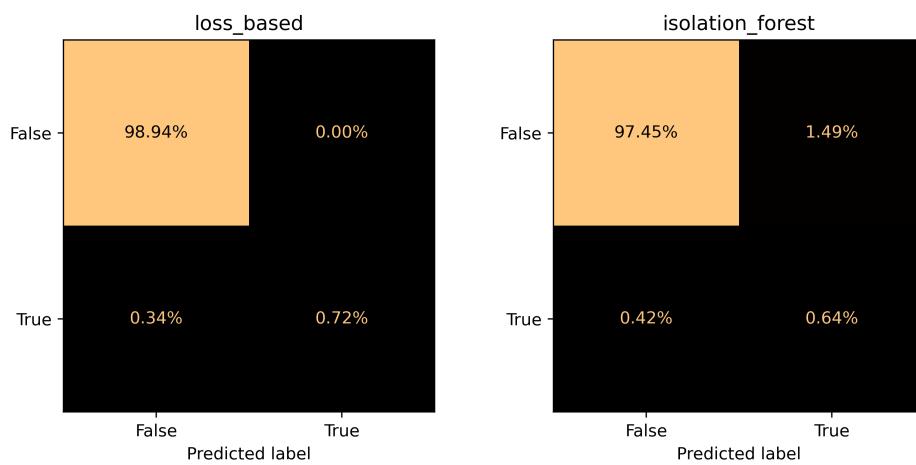


Figure 24: Confusion Matrices of the EfficientNetV2L Encoder

6 Discussion

7 Conclusion

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References

- [1] *AI&ML Training – AI Research Group*. en-US. URL: <https://ai.elte.hu/training/> (visited on 05/23/2023).
- [2] *AI Research Group – Artificial Intelligence & Data Science*. en-US. URL: <https://ai.elte.hu/> (visited on 05/23/2023).
- [3] Tamás Demus. *Mathematical Modeling Practice - Railway track defect detection*. original-date: 2022-12-02T20:47:30Z. Dec. 2022. URL: <https://github.com/demustamas/Mathematical-Modeling-Practice> (visited on 05/23/2023).
- [4] *Railway Track Fault Detection / Kaggle*. URL: <https://www.kaggle.com/datasets/salmaneunus/railway-track-fault-detection> (visited on 12/22/2022).
- [5] MÁV Központi Felépítményvizsgáló Kft. URL: <http://www.mavkfv.hu/index.php?lngchg=en&f=> (visited on 05/23/2023).
- [6] The MÁV Central Rail and Track Inspection Ltd. 25 years. 2021. URL: <http://www.mavkfv.hu/index.php?f=kfv25>.
- [7] Ritwek Khosla. *Auto-Encoders for Computer Vision: An Endless world of Possibilities*. en. Jan. 2021. URL: <https://www.analyticsvidhya.com/blog/2021/01/auto-encoders-for-computer-vision-an-endless-world-of-possibilities/> (visited on 05/24/2023).
- [8] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. <http://www.deeplearningbook.org>. MIT Press, 2016.
- [9] *Autoencoder*. en. Page Version ID: 1153796242. May 2023. URL: <https://en.wikipedia.org/w/index.php?title=Autoencoder&oldid=1153796242> (visited on 05/24/2023).
- [10] Karen Simonyan and Andrew Zisserman. *Very Deep Convolutional Networks for Large-Scale Image Recognition*. Tech. rep. arXiv:1409.1556 [cs] type: article. arXiv, Apr. 2015. URL: <http://arxiv.org/abs/1409.1556> (visited on 05/26/2023).
- [11] Kaiming He et al. *Deep Residual Learning for Image Recognition*. Tech. rep. arXiv:1512.03385 [cs] type: article. arXiv, Dec. 2015. DOI: <10.48550/arXiv.1512.03385>. URL: <http://arxiv.org/abs/1512.03385> (visited on 05/26/2023).
- [12] Mingxing Tan and Quoc V. Le. *EfficientNetV2: Smaller Models and Faster Training*. Tech. rep. arXiv:2104.00298 [cs] type: article. arXiv, June 2021. DOI: <10.48550/arXiv.2104.00298>. URL: <http://arxiv.org/abs/2104.00298> (visited on 05/26/2023).
- [13] *Anomaly detection*. en. Page Version ID: 1153438169. May 2023. URL: https://en.wikipedia.org/w/index.php?title=Anomaly_detection&oldid=1153438169 (visited on 05/26/2023).