Deep learning for brake squeal: vibration detection, characterization and prediction

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Abstract

Despite significant advances in numerical modeling of brake squeal, the majority of industrial research and design is still conducted experimentally. In this work we report on novel strategies for handling data-intensive vibration testings and gaining better insights into brake system vibrations. To this end, we propose machine learning-based methods to detect and characterize vibrations, understand sensitivities and predict brake squeal. Our aim is to illustrate how interdisciplinary approaches can leverage the potential of data science techniques for classical mechanical engineering challenges. In the first part, a deep learning brake squeal detector is developed to identify several classes of typical sounds in vibration recordings. The detection method is rooted in recent computer vision techniques for object detection. It allows to overcome limitations of classical approaches that rely on spectral properties of the recorded vibrations. Results indicate superior detection and characterization quality when compared to state-of-the-art brake squeal detectors. In the second part, deep recurrent neural networks are employed to learn the parametric patterns that determine the dynamic stability of the brake system during operation. Given a set of multivariate loading conditions, the models learn to predict the vibrational behavior of a specific brake system. It is found that those models can predict the occurrence and onset of brake squeal with high accuracy. Hence, the deep learning models can identify the complicated patterns and temporal dependencies in the loading conditions that drive the dynamical structure into regimes of instability. Large data sets from commercial brake system testing are used to train and validate the deep learning models.

Keywords: friction-induced vibrations, data science, object detection, time series classification, virtual twin

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Preprint submitted to Mechanical Systems and Signal Processing January 7, 2020
1. Introduction

Noise, vibration and harshness (NVH) issues in friction brakes are one of the most relevant customer claims in the automotive industry and omnipresent in rail vehicles [1, 2, 3, 4]. During the last two decades, research activities, cf. Figure 1 (a), have addressed fundamental instability mechanisms [5, 6, 7], design countermeasures [8, 9], advanced computational modeling [10, 11, 12, 13, 14], signal analysis [15, 16, 17, 18, 19, 20], uncertainty analysis [21, 22, 23, 24] and many more using experimental data and numerical models. However, until today the numerical prediction quality is in most cases unsatisfactory [25, 26]. The complex, non-stationary and multi-physic loads can drive automotive brake systems into states that are more prone to self-excited instabilities than others during operation. Generally, there is only small understanding for the actual instantaneous conditions that are responsible for the self-excitation in real-world braking systems. Decades of brake squeal research illustrate the fugitive character of this highly nonlinear [25], multi-scale [27] and chaotic [15, 28] phenomenon. In the contribution at hand,
deep learning techniques are employed to learn the functional relations between operational con-
ditions of the dynamical structure and its vibrational response. Whenever experimental systems
are studied [29, 30, 31], the occurrence of NVH-related vibrations has to be monitored. While
the detection of large-amplitude oscillations in sensor measurements of a brake system may seem
trivial, the automatic detection and classification of typical brake sounds is still challenging.
Identification of vibrations in measurements plays a crucial role in both research and industry:
in the era of big data and deep learning [32] large amounts of data are recorded which rule out
manual approaches. Cost-intensive design decisions, tailored research approaches and counter-
measures are based on the NVH assessment of a brake system, and thus on the NVH events
encountered during testing. Higher detection quality and accuracy is therefore of fundamental
interest.

Figure 1: Number of new publications per year for search items (a) brake squeal and (b) object detection from Web of
Science accessed on May 13th 2019. Search results include articles, proceedings, reviews and book chapters. While
brake squeal has been an active research field since 1995, deep learning has enabled the major break-through in object
detection from 2012 on.

The data sets used in this work have been recorded according to the SAE-J2521 test protocol
[33]. Quarter-car sections or smaller assemblies are subjected to the protocol on a test bench.
A matrix test is performed for variations of the type of braking (stop braking, drag braking) and
various combinations of operational parameters, such as rotational velocity, brake line pressure
and ambient air temperature. The time evolution of those loading parameters is recorded in the
form of time series data sampled at $f_s = 100$ Hz. The vibrational behavior is monitored through
a microphone located in proximity to the brake disc. For this signal, the sampling frequency
is $f_s = 51.2$ kHz. Figure 2 illustrates the relevant aspects of the data recorded during a single
braking and the our system understanding. In this example, a stop braking is performed and the
loading parameters as well as the vibrational response are measured as time series data. Dur-
ing the braking, a nonlinear evolution of the friction coefficient can be observed and the disk
surface temperature rises. The brake fluid temperature stays approximately constant because it
is more inertial and changes only slowly. Most of these multi-physic loadings and operational
conditions are mutually coupled. The combination of different loads, their instantaneous rate of
change as well as their history can constitute a dynamically unstable equilibrium of the mechan-
ical structure. As a result, friction-excited vibrations (FIV) grow and emit high-intensity sounds
through the vibrating disk. The radiated sound is captured by microphone. A short time Fourier
transform of the recorded signal allows to conduct a time-frequency analysis. In this case, tonal
and high-intensity FIVs arise after the first third of the braking. Several higher harmonics are
excited besides the fundamental frequency as visible in the spectrogram in the lower right in
From the nonlinear dynamics perspective, the self-excitation is rooted in a bifurcation of the equilibrium position as displayed in terms of the eigenvalues $\lambda$ in the upper right of the illustration. This aspect will be covered in more detail in the second part of this work. The second part illustrates how deep learning models can be employed to learn the mapping between the multivariate time-series-type loading measurements as input and the vibrational response as output. The first part is concerned with the detection and characterization of FIV in the microphone measurements. Here, it is of interest to identify typical sounds, their frequency-time location as well as their duration from univariate time series measurements as displayed in Figure 2 for the sound pressure level SPL.

Machine learning (ML) and deep learning (DL) have recently empowered breakthroughs in various research disciplines [34]. Furthermore, data-driven modeling and prediction can be considered to be omnipresent in every-day life today. However, to the knowledge of the authors, there has not been an attempt to leverage the potential of machine learning for friction-induced vibrations of brake systems so far. Therefore, our objective is to illustrate how those rather recent data-driven techniques can help to answer questions in the field of mechanical vibrations. In this
spirit, it is not our aim to present highly fine-tuned models and hunt for the best quality scores by extensive parameter searches. Instead, we strive to shed some light on novel pathways for data-driven treatment of friction-induced vibrations and foster further research in this field. We are well aware that even more data and careful model fine-tuning can improve the prediction quality presented hereafter. This work is separated into two major parts. A novel brake NVH sound detector is proposed in the first part. The design of a data-driven virtual twin for the brake NVH behavior is presented in the second part.

2. Part 1: Vibration detection and characterization

In brake NVH research on friction-induced vibrations, various vibration phenomena such as judder, creep-groan and squeal are well-known [35]. Tonal high-frequency (1-16 kHz) friction-induced vibrations, the so-called brake squeal, can be considered the most pressing issue in the automotive brake industry [36, 35, 37]. The difficulties to detect NVH events in testing data arise from various parasitic artefacts, signal distortion and noise contamination in the measured signal. Typically, the vibration behavior of a brake system is monitored by microphone and accelerometer measurements. The testing environment, whether a test bench or the vehicle, contributes to many parasitic vibration measurements. In case of the dynamometer, the motor, the ventilation and other external engines steadily contribute with a colored noise floor including aggregate-dependent periodicities. Furthermore, the operation of the brake system itself creates additional dynamics due to the rotation of the disk, piston actuation and resulting large scale motion of the complete system. During vehicle testing, the noise contamination is even larger due to all kinds of environmental noises, street excitation and additional sounds from other traffic participants. Hence, signals recorded during experimental testing are multi-scale and transient. Common self-excited vibration phenomena acquired during testing on NVH dynamometers hence only provide a model character of actual in-operation traffic brake noises. Yet, examples are depicted in Figure 3 to illustrate the plethora and complexity of friction-induced vibrations of brake systems. Highly-automated procedures to detect and classify those different vibrations are mostly limited to amplitude-based criteria and spectral methods using the Fourier transform. These approaches work well for tonal sounds with dominant periodicities, such as squeal, but fail for more complex vibration patterns. On the contrary, experienced engineers and researchers can visually identify those different NVH sounds with ease in spectrograms derived from the vibration measurements. Hence, in this work we propose a novel technique to detect and classify different classes of brake NVH sounds using recent deep learning techniques for object detection in images. Conceptually, the univariate vibration time series measurements are converted into two-dimensional representations in the time-frequency domain to transform the time series classification task into an image-based object detection task.

This part is organized as follows: first, state-of-the-art squeal detection approaches, their limitations and deep learning based computer vision techniques are re-visited. Next, we propose a novel NVH sound detection algorithm based on deep neural networks used for object detection in spectrograms. Results are shown for a large set of brake vibration measurements from automotive disk brake testing. First, the classification task is addressed, and in a second step the localization of individual sound classes in time and frequency range is presented. The performance of this novel technique is compared to classical approaches using a reference data set.

In the past, brake sound detection and deep learning based object detection have been completely separated fields of research. Before we illustrate our novel approach to combine those...
two disciplines, we shortly re-visit the core methodologies, opportunities and limitations of state-of-the-art procedures. Generally, the task of brake sound detection requires the identification of dominant characteristics buried in noisy, transient and multiscale vibration measurements. A wide range of scientific disciplines share the very general objective of finding specific patterns in audio or vibration recordings: In [39] baby cries were identified in noise-contaminated recordings. The authors show how a deep learning approach using convolutional networks outperforms a classical detector that is based on handcrafted features from Mel-frequency cepstrum coefficients. The authors in [40] study different convolutional neural networks for a bird call classification challenge involving more than 35,000 recordings and 1500 bird species. Here, raw audio signals and visual representations (spectrograms) of audio signals are processed to arrive at high detection rates. Flying drones were detected acoustically [41] using deep learning for environmental sound recordings and sleep quality was assessed via deep learning audio processing [42]. Similarly, among many other applications, screams and gunshots were detected using neural networks [43, 44]. However, most of these cases cover binary or multiclass sound classification tasks ("is there a sound of class A in the recorded signal?"). On the contrary, research on brake system FIV requires also the location of patterns in the frequency and time dimension.

Figure 3: Typical friction-induced vibrations from automotive disk brake system testing: (a) quiet braking, (b) monofrequent brake squeal, (c) multiple co-existing squeal events, (d) click sound of the pad, (e) so-called wirebrush sound involving multiple short impulses and chirps, and (f) broad-band noise artefact from the testing surrounding. Microphone recordings of the sound pressure level (SPL) and resulting spectrograms are displayed. Data were acquired during testings according to the SAE-J2521 [33] protocol on a NVH dynamometer.
(when does the sound occur, and in which frequency range?). This requirement renders the brake sound detection task more demanding.

2.1. Spectral squeal detection

![Schematic illustration of a conventional spectral squeal detector: (a) microphone measurement of the sound pressure level (SPL) as recorded during a braking. Using a sliding window approach, a series of amplitude spectra is computed to search for tonal events. (b) a tonal event is defined by the sharpness of the peak, i.e. its height above the surrounding frequency bandwidth. (c) the sound pressure level of candidate squeal frequencies $f_{sq}$ is tracked over the braking time to find the squeal duration and the squeal amplitude satisfying a minimal level such as 50 dB(A). The final squeal detection result is depicted in the spectrogram (d).]

Only few references can be identified that explain current approaches to detect the class of brake squeal sounds in recordings from microphones or acceleration sensors [45, 46, 47]. Generally, brake squeal is defined as a tonal sound in the audible frequency range above 1 kHz at perceivable amplitude. The tonal character restricts the vibration energy to being confined to a narrow frequency range, i.e. a sharp dominant and weakly damped peak in the signals Fourier transform. Typically, several conditions are posed on the amplitude, sharpness and duration of the vibration event to be identified as a squeal sound [45]. Figure 4 illustrates a spectral approach schematically. Using a sliding window approach, amplitude spectra are computed for successive instants of the vibration measurement. Peaks are identified in the spectrum and their sharpness is assessed. The tonal character of a peak is confirmed if its value exceeds a threshold value above the mean level in the 1 kHz band centered at the candidate peak frequency. All potential
tonal squeal frequencies are logged along time in the sliding window processing. As squeal frequencies may shift slightly over time, peaks are assigned to a single group if they do not differ by more than a specific frequency gap, e.g. ±100 Hz. For each frequency group, the duration of a tonal sound event above the critical sound pressure level, for example 50 dB(A), is evaluated. Very short events are discarded while interrupted sounds of the same frequency may be combined to a single event. The results are stored in log files containing the squeal frequency, start and end times as well as the sound pressure level. Those log files are used to assess the NVH behavior of a brake system, identify dominant instabilities and sensitivities against operational conditions. For comparison to neural network based classifiers, we implemented such a spectral squeal detector for this work. In the example displayed in Figure 4, the dominant squeal event can be detected easily based on the aforementioned spectral properties. However, several different friction-induced vibration phenomena render the spectral detection difficult: multiple co-existing tonal sounds, frequency and amplitude modulations, superposed broad-band noise and other artefacts from the testing environment can hinder a robust peak detection, see Figure 3. As a result, misclassifications may occur in the form of false positives FP (squeal detected even though there is none) or false negatives FN (no squeal detected even though there is one). Furthermore, detection and classification of no-squeal sounds is impractical using specific spectral properties. Thus, the limitations of spectral noise detectors are mainly given by wrong squeal detections and the missing flexibility to be extended to other.

2.2. Object detection in computer vision

Computer vision tasks can be roughly categorized as follows: image classification and localization involve only a single object which is to be recognized by the computer. In contrast, object detection and instance segmentation involve possibly multiple objects within one image, and are therefore more challenging. In this work we utilize object detection methods.

Prior to the triumph of artificial neural networks (see Figure 1 (b) before 2012), classical computer vision (CV) improved steadily by the use of increasingly complex handcrafted features. While [48] used cascades of low-level features for face detection, [49] introduced more complex oriented gradients for shape detection. Next, [50] proposed deformable templates and [51] used multi-resolution image features for better object detection. The annual ImageNet [52] and PASCAL [53] challenge for image classification and object localization illustrated the incremental improvements of conventional CV techniques using increasingly complex features and classifiers. In 2012, first neural network based approaches (AlexNet [54]) showcased their performance and flexibility in performing object detection tasks. Since then, deep learning methods dominate in those competitions owing to a substantially higher performance.

Deep learning computer vision approaches developed rapidly in recent years, following mainly two major branches that are interconnected: region proposal based and regression based methods [56]. The first branch is a two-step process including the task of bounding box regression (i.e. optimizing the correct size and position of the bounding box) and the task of object classification. Region proposals are generated first, and the classification of each proposal into a category

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1Common standardized data sets to benchmark novel models and algorithms are PASCAL, ImageNet and COCO (Common Objects in Context) [55]. PASCAL Visual Object Classification (PASCAL VOC) is comprised of 20 categories for object detection, classification and segmentation. This dataset features approximately 10000 annotated images for each annual challenge (2005 to 2012). ImageNet was released in 2013 and features 500000 annotated images with 200 categories for object detection. COCO by Microsoft has 80 categories for object detection and features more than 200000 annotated training images per annual competition.
is performed second. Region proposal based methods developed along R-CNN (regions with convolutional neural networks) [57], Fast R-CNN [58], Faster R-CNN [59], R-FCN (region-based fully connected networks) [60] and others. The second branch of methods achieves the regression task and the classification task at once, therefore greatly reducing the computational efforts. Regression based methods feature G-CNN (grid-based convolutional neural network) [61], YOLO (you only look once) [62] and SSD (single shot multi-box detector) [63]. All of the aforementioned models rely on convolutional layers as core building blocks for the network. However, several different network configurations are well-established nowadays. The AlexNet [54] is generally composed of five convolutional and three fully connected (FC) layers using rectified linear units (ReLU) as activation function. To reduce complexity, the inception module of GoogLeNet [64] relies on sparse convolutional layers and simpler pooling layers instead of FC layers. Residual networks (resnet) avoid the vanishing gradient problem and degradation by a modular structure that reduces the network error faster.

In the following, we propose a data-based detection technique to overcome the limitations of spectral detectors. In particular, we extend the capabilities of the novel detector to multiple prototypical sounds, which are not limited to high-frequency squeal events. Furthermore, we strive to reduce misclassifications by extensive training of the deep learning detector using a large database of brake sound recordings.

2.3. Deep learning brake sound detection

The conceptual core of this contribution is based on a) the human ability to identify several NVH sounds in spectral representations of measurements and b) recent advantages in computer vision driven by deep neural networks. Hence, if an experienced brake system engineer can visually identify several classes of sounds in a spectrogram, why should an artificial network, nowadays propelling scene interpretation in autonomous driving, not be able to do so as well? To access methodologies from computer vision, we first transform vibration measurements to images using the short-time Fourier transform. Then, image classification and object detection methods can be used for time-series classification and segmentation. The general aim of object detection is to locate objects in an image, label them by a class name and frame them with a bounding box. Figure 5 illustrates the general approach for training a deep learning object detection model for brake sound detection.

Several thousand vibration recordings acquired by microphone are available for training the novel classifier. As we strive for a supervised learning approach, the recorded vibration data needs to be labeled first. This step is performed manually by visual inspection of the spectrograms and listening to the microphone recordings. Bounding boxes with class labels are assigned to each sample. Annotations are not limited to a single class, such that multiple bounding boxes of different classes can be assigned to a single spectrogram when multiple NVH events occurred during this braking. In this work we consider four different classes, i.e. objects to be identified in the spectrograms:

- high-frequency squeal, see Figure 3(b) and (c), with minimum duration of $d = 0.5\, \text{s}$, minimum peak amplitude of $l = 50\, \text{dB(A)}$ and squeal frequency $1\, \text{kHz} < f_{sq} < 16\, \text{kHz}$;
- wirebrush sound involving various short-time sounds, see Figure 3(e);
- impulse-like click sound, see Figure 3(d), and
- broad-band noise artefacts of high amplitudes, see Figure 3(f).
As most of the brakings are quiet, only a fraction of the available data exhibit brake sounds. In total, 3,276 brake sounds remain for training, testing and evaluation of the different detectors. A set of 290 representative samples is kept aside for evaluation of the detectors, i.e. 3,076 annotated samples remain for training and testing of the deep learning models. A reference data set of 490 measurements is employed to assess the performance of conventional and deep learning detectors. The data set is constructed such that it reflects the general distribution of NVH sounds encountered during testing except for the class of quiet brakings which is typically highly over-represented. Specifically, the data set is composed of 200 quiet brakings (constituting the negative control), 200 squeal sounds, 50 wirebrush noises, 25 click sounds and 15 broad-band noise recordings. Each recording in the reference data set is a single-class image, i.e. there can be multiple events in a single image but they all belong to the same class. This set-up is beneficial for comparing the conventional squeal detector with the deep learning models.
2.3.1. Model configuration and training

Artificial neural networks feature a multitude of parameters, i.e. the weights connecting nodes and defining convolution kernels. Training denotes finding the optimal values for all parameters such that the network learns a decent mapping between input and output values. Hence, the training process is an extensive optimization challenge involving millions of parameters. We will restrict ourselves to a general introduction to the concepts of learning and refer to the multitude of literature on deep learning [32]. Most optimization strategies rely on the concept of backpropagating the model errors for finding the optimal network parameters: The training data set is comprised of input values and labeled output values, i.e. ground-truth data sets. Inputs are propagated through the network resulting in the predicted output. This output is compared against the ground truth output to define an error metric. During backpropagation, the contribution of each network parameter to the overall error is derived by partial derivatives. Based on the individual error contribution, the optimizer adapts each network parameter according to the learning rate. The process of feeding the training data through the network, backpropagating the error and subsequent weight adaptation is denoted as training. Training is stopped once an error tolerance is met, or the error does not decrease anymore, i.e. corresponding to a minimum of the error functional. Extensive training of the network may cause overfitting, such that the network over-adapts to the training instances, but does not generalize well for unseen data. The generalization quality is evaluated using the test set, which is not part of the training process.

We employ the concept of transfer learning to build deep learning brake NVH detectors. Hence, pre-trained models are selected as starting point of the training process. Particularly, two instances of the Faster-RCNN and a R-FCN model are considered. Region based convolutional neural networks (R-CNN) in their simplest form work in a two-step procedure: first, a large number of region proposals is generated through a selective search algorithm. Then, each region proposal, in form of a warped image, is fed into a CNN to compute a feature map. A classifier, such as a support vector machine (SVM) or fully connected network (FCN) can then be used to assign a class label, while a regressor is used to optimize the region proposal, i.e. the bounding box. Fast R-CNN architectures compute a single feature map from the image using a CNN, and then feed the features for each region proposal into the classifier-regressor unit. Hence, computing time is drastically reduced by computing the convolution only once and allowing for end-to-end training using a multi-task loss function. Further performance gains are achieved through Faster R-CNN architectures that use a region-proposal network (RPN) for proposing regions of interest directly from the CNN feature map. Region-based fully convolutional networks (R-FCN) rely on banks of position-sensitive score maps for each object category that are generated by a fully convolutional network. Again, region proposals are generated through a RPN, and position-sensitive pooling layers are applied to the score maps to identify objects in the input image. Hence, the central idea of R-FCN is to derive location-sensitive feature maps that account for characteristic image features being located at characteristic locations within the image. The FCN part of R-CNN models is removed, which results in faster inference time of R-FCN models compared to Faster R-CNN models. Both approaches are state-of-the-art object detection architectures and were thus chosen as candidate models for the brake sound detection task.

Each model is trained for 100,000 steps using a unit batch size. To increase the network’s robustness against overfitting, data augmentation strategies are used to horizontally flip, randomly crop, randomly pad the image and add random black patches. The learning rate is set to a constant value of 0.0003 for all models. The training set consists of 2,387 images and the test set...
consists of 599 images, corresponding to an 80 – 20 split.

2.3.2. Performance metrics

The performance of the conventional and the deep learning detectors are assessed using a manually labeled evaluation set. For classification tasks, the confusion matrix is used to report the number of true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN). The predicted labels are compared to the ground truth to fill this matrix. Various classification quality metrics are constructed from those values, such as

\[
\text{accuracy} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}
\]

\[
\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}
\]

\[
\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}
\]

\[
F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]

We measure the classification and detection performance by sensitivity and specificity. Sensitivity, also denoted as recall or true positive rate, measures the number of squeals that are correctly detected by the algorithm. On the other hand, specificity, also denoted as true negative rate, gives the number of recordings in which the detector correctly did not find a sound event. An over-sensitive detector will therefore have a high sensitivity, but a low specificity.

The developed models do not only return a class label for each prediction, but also a confidence score. This score can be used to rank the predictions of all examples. Then, the cumulative precision and recall can be computed for decreasing confidence values. The result is typically displayed in form of the precision-recall curve (PRC). A good detector exhibits high precision values even for increasing recall values, hence a decreasing number of false positives while the number of false negatives stays low. Practically, this means that also for lower confidence values the model still detects most of the positive objects without reporting too many false positives. The area under the curve (AUC) then measures the average precision (AP) for a single class of objects. For multi-class tasks the mean average precision (mAP) summarizes the overall performance of the classification model. Appendix B elaborates further on the PRC used in this work for object detection evaluation. For the deep learning models the minimum confidence level for reporting a predicted bounding box is set to \(C_t\) in the following sections. Lower confidence levels result in more false positive detections, while higher values lead to an increased number of false negatives, see Appendix C for the related studies and numerical values of \(C_t\). For the object detection class also the correct location of the bounding boxes have to be taken into account. The intersection over union (IoU) measures the overlap of the predicted bounding box and the ground truth bounding box and is considered as an additional metric for evaluating the object detection performance, see also Appendix B.

Generally, the scope of this work is to showcase the use of recent deep learning methods in classical engineering. Therefore, we do not strive for highly optimized models stemming from exhaustive hyperparameter searches. Instead, we illustrate the general capabilities of deep learning methods. We are well aware of more advanced models and the fact that our data set is rather small compared to the mentioned state-of-the-art object detection challenges.
Classification performance

Classification of a vibration measurement into one or multiple categories is an important aspect for automatic NVH data processing. Hence, in the first step we discuss the classification performance of various models and compare them to the state-of-the-art baseline, i.e. the conventional spectral squeal detector. The object detection outcome is transformed into a multi-class image classification task by neglecting the bounding box locations and only considering the predicted categories (‘is there squeal in the image?’). As the images of the reference data set are single-class images, we can assign a unique class to each image, and then compare ground truth and prediction based on the class label. Table 1 reports the results of different classifiers by their confusion matrix entries per category. Even though the spectral detector is designed only for squeal sounds, its performance in the three remaining classes is reported as well. Ideally, this detector would return zero true positives, zero false positives and 490 true negatives for the categories wirebrush, click and broad-band noise. False negatives and related metrics are not defined for those categories as the conventional detector can only report squeal sounds. Due to the class imbalance, accuracy values are not reported as they are biased towards the over-represented squeal class.

| classifier       | category   | TP  | FP  | FN  | TN  | recall | precision | F₁  | AP    | mAP    |
|------------------|------------|-----|-----|-----|-----|--------|-----------|-----|-------|--------|
| DL model 1       | squeal     | 149 | 68  | 7   | 266 | 0.96   | 0.69      | 0.8 | 0.68  | 0.73   |
| (faster R-CNN incep) | wirebrush  | 33  | 1   | 17  | 439 | 0.66   | 0.97      | 0.79| 0.69  |        |
|                  | click      | 23  | 8   | 2   | 457 | 0.92   | 0.74      | 0.82| 0.88  |        |
|                  | artefact   | 10  | 0   | 5   | 475 | 0.67   | 1.00      | 0.80| 0.68  |        |
| DL model 2       | squeal     | 149 | 76  | 7   | 258 | 0.96   | 0.66      | 0.78| 0.72  | 0.80   |
| (faster R-CNN resnet) | wirebrush  | 38  | 3   | 12  | 437 | 0.76   | 0.93      | 0.84| 0.78  |        |
|                  | click      | 22  | 6   | 3   | 459 | 0.88   | 0.79      | 0.83| 0.87  |        |
|                  | artefact   | 12  | 0   | 3   | 475 | 0.8    | 1.00      | 0.89| 0.81  |        |
| DL model 3       | squeal     | 146 | 76  | 10  | 258 | 0.94   | 0.66      | 0.77| 0.68  | 0.55   |
| (R-FCN resnet)   | wirebrush  | 26  | 1   | 24  | 439 | 0.52   | 0.96      | 0.68| 0.57  |        |
|                  | click      | 21  | 0   | 4   | 465 | 0.84   | 1.00      | 0.91| 0.85  |        |
|                  | artefact   | 1   | 0   | 14  | 475 | 0.07   | 1.00      | 0.12| 0.1   |        |
| spectral         | squeal     | 156 | 177 | 0   | 157 | 1.00   | 0.47      | 0.64| 0.63  |        |
|                  | wirebrush  | –   | –   | –   | 440 | –      | –         | –  | –    | –      |
|                  | click      | –   | –   | –   | 465 | –      | –         | –  | –    | –      |
|                  | artefact   | –   | –   | –   | 475 | –      | –         | –  | –    | –      |

Table 1: Classification performance of the spectral detector and three deep learning (DL) models evaluated on the reference data set containing 200 quiet brakings, 200 squeals, 50 wirebrush sounds, 25 click sounds and 15 broad-banded artefacts. Quality metric recall, precision, F₁, average precision AP and mean average precision mAP (computed from precision-recall curve) are evaluated.

The conventional spectral squeal detector represents the baseline model for this study. As being designed for squeal detection, the classification performance for the other categories cannot be evaluated. It can be observed that this detector has a very high false positives rate. Hence, it tends to detect squeals in either quiet brakings, or brakings that show a different brake sound such as wirebrush. Obviously, this characteristic crucially depends on the hyperparameters of the detector, such as the minimal peak sharpness, minimal sound pressure level, minimal sound
duration, spectral and temporal gap allowance among others. However, for practical employment in research and design, those spectral detectors are typically designed to be over-sensitive in order to avoid false negatives and to not overlook possible NVH issues. As a result, the detector exhibits no false negatives, i.e. finds all squeal events, for the reference data set studied here.

Considering the deep learning detectors, all models achieve good classification performances for all categories. Generally, the false positives rate is high for the squeal category, whereas the false negatives rate is higher for the wirebrush category. The squeal classification performance is similar for all ML models and reach scores up to $F_1 = 0.8$. For the three other categories, models 1 and 2 outperform model 3 by a significant degree. Especially, model 3 exhibits a high false negatives rate for noise artefacts and wirebrush, both representing spatially extended objects in the spectrograms. Overall, the faster R-CNN resnet architecture (model 2) performs best in this study with similar squeal classification ability as the conventional approach and high classification quality for the remaining object classes.

Figure 6 depicts the precision-recall curves for the classification task and all three deep learning models. While the performance for squeal classification is rather similar for all models, the conventional squeal detector shows poorer performance for recall values larger than 0.3. The superior overall performance of model 1 and model 2 becomes obvious for the wirebrush and artefact categories. Here, the PRC of model 3 drops significantly earlier for increasing recall values, thus representing poorer performance. Model 2 (mAP = 0.8) achieves the best overall score, followed by model 1 (mAP = 0.73) and model 3 (mAP = 0.55).

Concluding, the deep learning based detectors showcase their improved capabilities compared to the classical approach when considering the brake sound classification task. While the single-class spectral methods have to be designed for a low specificity resulting in many false positives, the deep learning detectors can be designed towards high sensitivity owing to multiple class labels. In the next step, the brake noise localization in time and frequency is evaluated.

2.3.4. Object detection performance

We evaluate the performance taking the frequency and time localization into account, i.e. considering not only the bounding box label but also its location. Table 2 reports the average precision values per class and the resulting mean average precision per detector. The underlying precision-recall curves can be found in Appendix D. The minimum confidence values for reporting a predicted object are equal to the ones chosen for the image classification task.

Similarly to the classification task, model 2 performs best. For the squeal category this detector shows slightly higher AP values than models 1 and 3. In the other categories, even higher quality metrics are observed. Model 3 fails to detect artefacts correctly, and also shows poorer performance for the wirebrush and click class. Model 1 exhibits good overall performance in all categories, but cannot reach model 2. However, these detection quality metrics must be considered with care: the squeal and click objects are rather slim objects, while wirebrush and artefacts may cover substantial areas of the spectrogram. Hence, the imposed IoU thresholds are much stricter for the slim objects than for the spatially extended objects which may create a bias.

Figure 7 depicts a selection of qualitatively different brake sounds and the resulting detection results obtained using model 1. Most of the bounding boxes are predicted at the correct locations and all class labels are correct. The model is capable of detecting single and multiple events in the spectrograms and returns high confidence scores. For the squeal category, it can handle temporal

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2See Appendix B for more details
Figure 6: Precision-recall curves (PRC) for the deep learning detectors evaluated for the reference data set classification task

| classifier          | category | AP_{50} | AP_{75} | AP_{90} | mAP_{50} | mAP_{75} | mAP_{90} |
|---------------------|----------|---------|---------|---------|----------|----------|----------|
| ML model 1          | squeal   | 0.66    | 0.66    | 0.60    | 0.66     | 0.65     | 0.59     |
| (faster R-CNN inception) | wirebrush  | 0.57    | 0.54    | 0.36    |          |          |          |
|                     | click     | 0.74    | 0.74    | 0.72    | 0.67     | 0.67     | 0.67     |
|                     | artefact  | 0.67    | 0.67    | 0.67    |          |          |          |
| ML model 2          | squeal   | 0.68    | 0.68    | 0.62    | 0.69     | 0.67     | 0.55     |
| (faster R-CNN resnet) | wirebrush  | 0.61    | 0.51    | 0.19    |          |          |          |
|                     | click     | 0.80    | 0.80    | 0.71    | 0.69     | 0.67     | 0.55     |
|                     | artefact  | 0.69    | 0.67    | 0.55    |          |          |          |
| ML model 3          | squeal   | 0.66    | 0.65    | 0.60    | 0.43     | 0.39     | 0.34     |
| (R-FCN resnet)      | wirebrush  | 0.44    | 0.30    | 0.16    |          |          |          |
|                     | click     | 0.55    | 0.55    | 0.55    | 0.07     | 0.07     | 0.07     |
|                     | artefact  | 0.07    | 0.07    | 0.07    |          |          |          |

Table 2: Object detection performance measured by average precision per class (AP) at IoU levels 50%, 75% and 90% and resulting mean average precision (mAP) for each deep learning classifier

gaps, see case (c), for a single squeal frequency as well as spectral gaps, i.e. multiple co-existing squeal events separated in the frequency direction such as in (f). Multi-class predictions are also successful, see (e). In a last step the bounding box coordinates can be reported in terms of...
temporal, i.e. duration $d$, and frequency information. For the squeal class, the squeal frequency $f_{sq}$ is read from the bounding box center in vertical direction. As the bounding box may not be perfectly centered around the true squeal frequency, the conventional squeal detector has a higher precision in reporting the frequency value. The amplitude value $l$ can be read from the intensity map used for creating the spectrogram plot.

![Spectrograms](image)

**Figure 7:** Exemplary results of the deep learning brake sound detector (model 1) applied to six microphone recordings. Sound events are correctly detected and located in the spectrograms with high confidence scores. The detector can handle single class images, cf. (a-d), multiple events per image, cf. (f), and multi-class images, such as (e). The low intensity squeal in (c) is successfully identified, but the first click sound in (d) at 3.8 s is missed, therefore representing a false negative.

To be employed in a real testing environment, the detection models have to perform at high
speed. All of the networks discussed before were trained on a GPU-supported laptop. While training time for $10^6$ epochs took approximately a complete day for each model, the inference time is rather short: On average, 0.17 s per recording for model 1, 0.45 s per recording for model 2 and 0.24 s per recording for model 3 were measured on this machine. Even if measuring wall time tends to be very specific to system configurations, loads and other effects, these numbers may give a good general impression about the speed of the proposed deep learning detectors.

Future research activities are possible in two major aspects of the proposed methodology. First, other detection models may be tested for their applicability and performance. Here, we think of other deep learning architectures, such as YOLO and others, as well as conceptually different approaches such as classical CV methods for edge detection, such as the Canny edge detection filter [65], which would be applicable for squeal and click sound localization. Second, fine-tuning of the deep learning models may leverage their full potential and increase the detection quality even more. A systematical hyperparameter optimization and additional data augmentation is required to train the optimal detector. Plus, as a dogma in deep learning says: ‘Data beats algorithms’ - more data will help to increase the robustness of the detection models. However, in this work we aimed at showcasing the opportunities of deep learning for brake squeal research rather than to develop a highly fine-tuned model. Finally, a combination of conventional and novel detectors is possible to cross-validate the detection of a single method.

3. Part 2: Vibration prediction

This part aims at learning patterns from large data sets acquired during experimental NVH (noise, vibration, harshness) testing on brake dynamometers. Specifically, the time evolution of several loading conditions, such as disc velocity and brake line pressure, are considered as input to a deep artificial neural network for predicting the instantaneous vibration behavior of the system in terms of squeal sounds. The particular neural network architecture enables the deep learning model to learn patterns that incorporate the salient features of dynamics, i.e. the dynamic evolution of the inputs given by their instantaneous value as well as their history.

The objective of this work is to study whether there is a deterministic relationship between the loading conditions of the brake system and its vibrational behavior. Specifically, the input measurements are sparse in a sense that only a limited number of loads and operational conditions can be captured during experimental testing. For some systems, these parameters may represent dominant bifurcation parameters that allow to identify instability conditions. However, even for a small number of loads measured during testing, the combinatorial complexity grows out of scope for manual identification of critical conditions. Exemplary, a falling friction-velocity characteristic at a certain contact normal load increase for a specific combination of disk temperature and relative air humidity may constitute a squeal-critical condition. Finding such conditions manually is intractable, but seems conceptually possible using modern machine learning approaches. Generally, machine learning aims at approximating complex functions for an input-output relation given by historic data. The model learned during a training phase can be used to make predictions on new input data. Furthermore, the function approximation can be analyzed for obtaining better insights into the causal relations learned by the model. In this work, the NVH response represents the output of the brake system for a set of loading conditions that form the model input. If the system’s vibration response can be predicted from those inputs,
the identification of instability regimes is possible, which in turn allows predicting squeal for a
given loading scenario.

This part is organized as follows. First, brake system vibrations are re-visited in a brief re-
view on current approaches to understanding and reducing the phenomenon of squeal before
an overview on time series classification techniques and recurrent neural networks are introduced. Then, data
pre-processing steps and a hyperparameter study are discussed to find an optimal network con-
figuration for the given classification task. Classifiers are trained on four data sets in two different
set-ups to predict if a given set of loads will cause squeal, and to predict when the vibrations will
be excited. Lastly, models trained on one system are evaluated on a different brake system to
investigate if the network has learned underlying dominant patterns that govern squeal across
different brake systems.

3.1. Input-output behavior of dynamical systems

From a conceptual perspective, the friction interface provides energy input to a dynamical
structure composed of multiple parts and assembled by mechanical joints [66, 67, 68] which add
significant amounts of damping and nonlinearity [69, 70]. Furthermore, the structure experiences
external loads, such as excitations from the road, and changing environmental conditions, such
as changing ambient temperatures. Stability, and thus the vibrational behavior of the structure, is
governed by the flow, localization and balance of energy between sources and sinks. The overall
stiffness and damping properties of the structure determine the energy flux and hence the system
dynamics. Due to temperature-dependent material parameters, non-linear force-displacement
characteristics and the ever-changing frictional interfaces [71, 72], stiffness and damping can
vary and change the overall system stability [73]. As a result, the nonlinear structure may exhibit
a rich and complicated bifurcation behavior with respect to one or multiple parameter variations
[6, 74]. Given the complexity of the system, one cannot assume a single parameter, such as
the relative sliding velocity of the brake pad, to generally initiate instability and dominate the
overall bifurcation behavior. Instead, combinations of various parameters, their instantaneous
changes as well as their past values, are more likely to drive the system dynamics into different
stability regimes. The rich corpus of research on frictional systems has identified various
mechanisms for instability [75], such as stick-slip [75, 76], a negative friction slope [77, 78, 79]
and mode-coupling [5, 80, 7]. However, most of these mechanisms are limited to single-point
contacts in idealized model systems. Spatially distributed contacts are well-known for adding
aspects of synchronization [81], multistability [82, 83] and localization [84, 85], i.e. complicat-
ing the picture of stability drastically. Previous work [19] on extracting the instantaneous growth
rates, i.e. quantifying linear stability and instantaneous damping, from experimental data illus-
trates high sensitivity of the effective damping with respect to loading conditions. Along with
the aforementioned parametric changes to the system properties, it remains a difficult task to
identify and understand the underlying parameters and conditions that drive a real brake system
into instability. Besides model parameter uncertainties [86], this is one of the major reasons for
the poor squeal prediction quality of numerical simulations even today [25]. The inherently tran-
sient [87] and multivariate input (loads) - output (vibration response) behavior of a brake system
is studied in this work using deep learning techniques tailored for such a scenario. Physical
measurements of various quantities related to the operation of the brake system are considered
as proxies that drive main stiffness and damping variations [88, 89] of the system. Formally,
one may express this system understanding in terms of parametric velocity-dependent \( P \)
and displacement-dependent \( Q \) model terms, strongly nonlinear forces \( f_{nl} \) from the friction interface,
from joints and from geometric constraints, as well as external forces \( f_{ext} \). The parameter vector
\[ M(\Xi)\ddot{x} + P(\Xi)\dot{x} + Q(\Xi)x + f_{nl}(x, \dot{x}, \Xi) = f_{\text{ext}}(\Xi, t), \quad \Xi = f(x, \dot{x}, t) \in \mathbb{R}^m \] (2)

Here, the time-variant loads of the brake system are considered to constitute the multivariate and time-dependent parameter vector \( \Xi \in \mathbb{R}^m \). For a complete system description, the parameter vector would have to contain a, probably, uncountable number of \( \tilde{m} \) quantities that can act as a bifurcation parameter for the system dynamics. Hence, one of the major objectives of this work is to find out whether the \( m \) loads measured during the test campaign represent dominant members of the parameter vector \( \Xi \) and hence allow for instability prediction. Thinking of brake squeal regarding input-output behavior is motivated by the architecture of neural networks whose primary task is the learning of a function approximation between input and output values. We still consider self-excitation through flutter or a falling friction slope, and not external forcing, as the instability mechanisms of brake squeal. However, to initiate instability, parametric changes in the system are required. Those changes of parameters are referred to as the inputs, and the vibrational response as the output in the aforementioned system description.
Figure 8 illustrates loads recorded during a single braking in the left panels and the resulting vibrational response in the right panels. It becomes obvious that braking and brake squeal is a highly transient and multi-physic process. Furthermore, multiple temporal scales are involved on the slow (loads) and fast (vibrations) scale. There may exist multiple regions of instability in the parameter space $\Xi \in \mathbb{R}^m$ with possibly complicated boundaries. Manual discovery of multi-dimensional and time-dependent patterns leading to instability is impractical, if not impossible. Hence, recurrent neural networks, to be introduced in the following, are employed to map the time-variant loading parameters to the squealing behavior, i.e. to learn the temporal patterns in the multivariate loading conditions that cause friction-induced instabilities of the individual brake systems. Again, we emphasize that the parameter space spanned by the acquired loading signals during experimental testing cannot be expected to carry all relevant pieces of information that are required to unfold the instability regimes completely. Though, the available data may contain major dimensions of the actual parameter space $\Xi \in \mathbb{R}^m$. The format of the data recorded during testing takes the form of time series. In the following section, time series classification and deep learning-based approaches are introduced.

3.2. Time series classification

Sampling a continuous quantity $s(t)$ at time instants $t_i$ results in an univariate time series $s$ of length $n_t$

\[
s = (s(t_1), s(t_2), \ldots, s(t_{n_t})), \quad n_t \in \mathbb{Z}^+, \tag{3}\n\]

where a uniform sampling $t_{i+1} = t_i + \Delta t$ is assumed. Multivariate time series $S(t)$ measure multiple quantities in a contemporaneous fashion. The sequential order of the time series entries carries information about derivatives and history, and must hence be taken into account during time series processing. Time series classification (TSC) denotes the task of assigning a class label to a time series. Bagnall et al. [91] propose to cluster TSC approaches into three main categories. Distance-based classifiers [92], also referred to as instance-based classifiers, measure similarity between different time series in terms of Euclidean or other distances and then assign class labels. Dynamic Time Warping (DTW) [93] can be considered state-of-the-art for this class of classifiers. The second class of feature-based classifiers [94] transforms the dynamic time series into a set of static values that describe certain properties of the sequence, e.g. the mean, variance or others. To derive discriminative features, expert domain knowledge is required. Those static features can then be fed to any conventional machine learning algorithm to assign a class label to a given time series. Third, direct approaches [95] learn representative high-level features themselves and do not rely on manually hard-coded feature extraction recipes. Hence, direct approaches are the less interpretable and constitute black-box models that receive the raw time series as input and output the predicted class label. Direct approaches do not require a-priori domain expert knowledge to extract discriminative features and are generally able to learn complex temporal patterns. As a downside, larger amounts of data are required during the training phase owing to the increased model complexity. The architecture of direct approaches can be constituted of convolutional networks (CNN) [96, 97], recurrent neural networks (RNN) [98] or variations of these [99]. Rather recent works propose to convert the input time series into images and then use the large corpus of deep learning techniques from computer vision to accomplish the TSC task [100, 101, 102]. In this work we propose to use a variation of RNNs, so-called Long-Short-Term Memory Networks (LSTM) [103], for the brake squeal prediction task.
3.3. Recurrent neural networks

Recurrent neural networks are tailored for sequence learning, i.e. deep learning tasks for inputs with sequential character. RNNs take the sequential character into account by creating a time dependent memory state \( h(t) \) that carries information about previous states. At time \( t \), the memory state is evaluated with respect to the memory state of the previous time step

\[
h(t_i) = \sigma(h(t_{i-1}) , S(t_i))
\]

where we assume a multivariate time-series input as in Equation (3). Hence, RNNs are capable of taking the history of the time series into account when evaluating the current value at time \( t_i \).

Analogously to a multilayer perceptron network (MLP), the RNN modifies the inputs according to a weight matrix \( W(1) \). The result is added to the memory state of the previous time step, which is weighted with \( W(2) \). The sum of both is referred to as *net input* and is evaluated at time instance \( t_i \)

\[
h(t_i) = \sigma(W(1)S(t_i) + W(2)h(t_{i-1}) + b)
\]

where \( \sigma(\cdot) \) is a nonlinear and differentiable activation function and \( b \) denotes bias values. The output of \( \sigma(\cdot) \) represents the updated memory state for the current time step. It is weighted again with another weight matrix \( W(3) \) to generate the output at this time step and is forwarded in time for the calculation of the subsequent memory state. This time-unfolded representation of a recurrent network layer is shown in Figure 9. Processing the input \( S \) results in a multivariate output \( Y(t_i) \), which again might be used as input to the next layer. Multiple RNN layers can be stacked to generate a deep network architecture.

![Figure 9: Representation of a recurrent neural network unrolled along time](image)

Figure 9: Representation of a recurrent neural network unrolled along time. A multivariate time series \( S \in \mathbb{R}^{m \times n_t} \) serves at each time step \( t_i \) multiple features \( S_1(t_i) \cdots S_m(t_i) \) as input. After weighting \( W(1) \) and processing inside the cell, the memory state is updated. It is weighted again \( W(2) \), to create a multivariate output at each time step \( Y(t_i) \) and is fed forward to the next time step. The output \( Y \) may serve as input for an additional stacked layer.

When training RNNs, an adapted backpropagation algorithm is put to use, called backpropagation through time (BPTT) introduced by Werbos [104]. The difference between the network prediction \( \hat{Y}(t_i) \) and the desired output, i.e. the ground truth, is used to calculate a loss
value \( L \). Following classical error backpropagation, the contribution of each model weight to the overall loss is determined by partial derivatives of the loss with respect to each network parameter. The sum of derivatives for all time steps is then used to calculate adapted weights. The BPTT algorithm in recurrent neural networks can give rise to the vanishing gradients effect \([103, 105]\). Here, the partial derivative of the loss with respect to an input \( S(t) \) decays exponentially, becoming more severe the farther away \( t \) is located from \( t_i \) in time. Hence, the optimizer is not able to take information from all preceding time steps into account when updating the weights. This effect results in a short-term memory for basic RNNs and an incapability to respect long term time correlations. Therefore, modifications of the RNN architecture were proposed to address vanishing gradients. The most popular variations are the long short-term memory networks (LSTM) by Hochreiter and Schmidhuber \([103]\) and the gated recurrent unit (GRU) by Cho et al. \([106, 107]\). To surpass the vanishing gradient problem, the LSTM unit holds a second memory state, the so-called cell state \( c \). This state is modified with two gates, the forget gate causing information to be deleted from the network, and the input gate that adds new information from the input and the memory state. The resulting state is forwarded in time with the memory state and the input to form the new memory state as well as the output.

A common application of RNNs and their modifications has been the analysis of human centered sequential data as used in speech and handwriting recognition \([108, 109, 110, 111]\). Furthermore, they can be used for medical application, e.g. for analyzing ECG data \([112]\). In the mechanical engineering discipline, only few application cases have been reported, such as for predictive maintenance \([113]\), system health monitoring \([114, 115]\) and fault diagnosis for rotating machinery \([116]\). Due to their success in the aforementioned mechanical engineering related problems, we deem RNNs as viable tool for analyzing brake squeal data.

### 3.4. Data sets

We study four different data sets \( A, B, C, D \) in this work. All data sets stem from commercial testing according to the SAE-J2521 procedure \([33]\) on a NVH dynamometer. Squeals are detected in the microphone recordings for a minimum squeal duration of \( d_{sq} = 0.5 \) s and a minimum sound pressure level of \( l_{sq} = 55 \) dB(A). Data sets \( A \) and \( B \) stem from a family of brake systems that are similar in terms of geometry and performance. Like-wise, data sets \( C \) and \( D \) stem from a significantly different brake system. Hence, rather similar dynamic behavior can be expected for members of the same family, while large differences between families will not be surprising. However, due to the elusive character of brake squeal and multiple sensitivities, such assumptions must be confirmed by the analysis.

Figure 10 depicts the empirical cumulative distribution function of the braking durations and the squeal durations. While the braking durations are mostly prescribed by the testing procedure, the squeal durations arise from the self-excited instabilities and thus differ between the data sets. The two families of brake systems are clearly visible: systems \( A \) and \( B \) exhibit squeal sounds of similar duration distributions with more than half of the sounds being longer than \( \approx 5.5 \) s. Systems \( C \) and \( D \) show significantly shorter squeal sounds.

All relevant characteristics of the data sets are summarized in Table 3. The number of brakings and the squeal ratio are provided to give a general impression of the data sets and the uneven class distributions. Designed for quiet operation, the brake systems typically exhibit only a small fraction of squealing brakings. For this study particularly unstable brake systems were selected to obtain more samples for squealing brakings. Still, class imbalance can be observed which needs to be taken into account in the data splitting and classification scoring. For each braking, the eight loading conditions of disk velocity \( \Omega \), brake line pressure \( p \), brake torque \( M \), friction
coefficient $\mu$, disk surface temperature $T_{\text{rot}}$, brake fluid temperature $T_{\text{fluid}}$, ambient temperature $T_{\text{amb}}$ and relative humidity $H$ are available as time sequences. Furthermore, for each time step the binary one-hot encoded vibration label squeal / quiet is available as a time series. Figure 8 depicts those signals for a single braking in data set A.

![Figure 10: Left panel: empirical cumulative distribution function (ecdf) of the brake durations in data set A. The right panel depicts the ecdf of the squeal durations in data sets A, B, C and D. Characteristic quantiles are marked for data set A for which more than half of the squeals are longer than 5.5 s and 75% of the squeals are longer than 2.49 s](image)

| data set | $N$ | $N_{\text{squeal}}$ | $d_{\text{sq}}(\text{ecdf} = 0.25)$ [s] | $d_{\text{sq}}(\text{ecdf} = 0.50)$ [s] |
|----------|-----|---------------------|----------------------------------|----------------------------------|
| $A$      | 1206| 487                 | 2.49                             | 5.64                             |
| $B$      | 1206| 227                 | 1.97                             | 4.93                             |
| $C$      | 1206| 347                 | 1.32                             | 1.80                             |
| $D$      | 1889| 237                 | 0.97                             | 1.57                             |

Table 3: Characteristics of the data sets studied in this work: number of brakings $N$, number of squealing brakings $N_{\text{squeal}}$, squeal durations $d_{\text{sq}}$ and their 25% and 50% quantiles as displayed in Figure 10.

As in every machine learning pipeline, also the presented data sets require some pre-processing. Lengths of the recorded brakings vary from 2 to 10.5 seconds. As the training and performance of LSTM networks can be significantly facilitated through equal length inputs, a sliding window pre-processing step is introduced. The input and output sequences are segmented into windows of $w$ samples. The shift parameter $h$ denotes the number of samples by which the windows shift and $(w-h)$ provides the window overlap. Observations at the end of sequences are zero-padded to full length $w$ if they are longer than half the window size. Shorter sequence remnants are omitted. Depending on the choice of $w$ and $h$, the number of observations in the data sets can be significantly increased. Even if LSTMs are designed to learn long-time correlations, it is physically unknown which time history is required to predict the onset of squeal at the current time instance. The instability may be rooted in an instantaneous conditions, but can also be initiated through load history effects that require the consideration of longer sequences. Hence, the sliding window parameters are treated similarly to hyperparameters of the network. Window lengths of 200 and 400 samples, i.e. 2 and 4 s, are considered and overlaps of 0%, 25% and 50% of the window length are studied.
3.5. Virtual NVH twin results

Given the four data sets studied in this work, we aim to answer two fundamental questions using deep learning for the sequential loading and system response data:

1. Is brake squeal predictable from the recorded operational conditions using deep learning?
2. If squeal is predictable, is there an underlying mechanism that is immanent in multiple brake systems irrespective of geometry and configuration?

This work is a first approach to providing better insights into brake squeal using deep learning. As such, we do not strive to extensively fine-tune the classification models for maximum prediction quality. Instead, we demonstrate general approaches and directions for future research. All statements refer to the data sets studied in this work, and may vary from brake system to brake system. First, hyperparameter studies are presented to find an appropriate model architecture for the multivariate time series classification task. Then, the results are presented for two different network configurations and for four data sets. Finally, cross-evaluation studies evaluate the generalization properties of a classification model that was trained on one brake system and is then employed to predict the dynamic behavior of another brake system.

3.5.1. Model architecture studies

Finding an appropriate model configuration that is complex enough to capture the dominant patterns in the data without showing overfitting issues remains a tedious task in deep learning. In this work, we use a coarse grid search to determine the number of hidden LSTM layers, the number of LSTM units and the batch size value which achieve the best classification performance. Fully connected layers (FC) are utilized to create the output. Additionally, the data pre-processing with sliding window length $w$ and shift size $h$ is incorporated into the hyperparameter grid search. For the grid search, each model is trained for 200 epochs using the adam optimizer and binary cross-entropy as loss. Due to the high variability and nonlinearity of the brake squeal phenomenon, we expect rather complex networks to be necessary for successful prediction of the structural response. However, deep models exhibit the risk of overfitting. To prevent the latter, drop-out at a rate of 0.1 is used for the LSTM cells. Prediction performance is measured by Matthews correlation coefficient MCC \cite{Matthews1975} firstly proposed in biochemistry

$$\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (6)$$

that implicitly takes class imbalance into account. The MCC ranges from $(-1)$ to $(1)$, where $\text{MCC} = -1$ indicates complete disagreement and $\text{MCC} = 1$ indicates perfect classification. To account for the rather small data sets, three-fold cross-validation is employed to evaluate the generalization of the models. The grid search is performed on data set A, and the selected architecture is re-used for all data sets. Otherwise, comparison of performance for different data sets would not be possible in the cross-evaluation section. Generally, the hyperparameter study is performed to obtain a first overview on the required model complexity. It is very likely that extensive hyperparameter optimization will further improve the classification scores. Appendix E and Appendix F report the complete results for all 108 hyperparameter combinations in two classification scenarios: First, a single label is assigned to the loading input sequences, such that the model will predict whether an observation of loading sequences will cause squeal or not. Following the input and output dimensions involved in this setting, we refer to this classification
case as sequence-to-scalar. As a second approach, sequence-to-sequence classification is studied. The related models output a binary label for each time step, such that the output indicates at which time instances squeal is predicted to occur. In sequence learning, such sequential output is typically referred to as 'time-distributed labels'. Figure 11 depicts the two classification scenarios. The studied model architectures are given in Table 4. For the sequence-to-scalar classification, large batch size values of 256 and 256 LSTM units turn out to be the main driver for performance gain. Adding a second LSTM layer does not substantially improve the score, so a single LSTM layer is chosen. The sequence pre-processing parameters for the sliding windows have only a secondary impact. A window length of 200 samples with 25% overlap is chosen. The resulting model achieves a mean MCC value of 0.74 in a three-fold cross validation on data set A in the 300 epochs of training during the hyperparameter study. Overfitting was not observed for any of the models in the hyperparameter study, see Figure E.16.

For the sequence-to-sequence classification models, qualitatively similar behavior can be observed. Large numbers of LSTM units per layer are the main driver for increased performance, as well as large batch size values. Adding a second LSTM layer does not increase the classification score. Contrary to the first case, the sequence length of $w = 400$ is found to be the better choice for the sequence-to-sequence mapping. A different optimizer, such as stochastic gradient descend, does not improve the prediction quality here.

### 3.5.2. Squeal prediction using a sequence-to-scalar classifier

The final classifier is built using a single LSTM layer comprising 256 units, 0.1 dropout rate, adam optimizer, binary cross-entropy loss and input sequence lengths of $n_t = 200$ samples
Table 4: Model configurations studied in the hyperparameter search for the sequence input length $n_t = w \in [200, 400]$, number of LSTM units $n_{units} \in [64, 128, 256]$ and number of LSTM layers (either only first or both) using batch sizes of $[16, 64, 128, 256]$ with 25% overlap for each data set using a stratified 70-30 training-validation split. In contrary to the hyperparameter study, longer training for 500 epochs is used to train the optimal model. Figure E.15 in the Appendix displays the MCC curves for the training and validation set to demonstrate that the models are not overfitting. To obtain more representative results and reduce the potential bias caused by the data splitting, ten individual models are trained for each data set. For these models, the average validation MCC and its standard deviation are reported in Table 5.

| data set | training set size | validation set size | MCC mean ± std |
|---------|-------------------|---------------------|----------------|
| A       | 5354              | 2295                | 0.78 ± 0.02    |
| B       | 5325              | 2283                | 0.72 ± 0.03    |
| C       | 5462              | 2342                | 0.65 ± 0.02    |
| D       | 8614              | 3693                | 0.64 ± 0.03    |

Table 5: Sequence-to-scalar classification result for all data sets using a fixed network configuration. Ten models were fitted per data set, and the average and standard deviation of the validation scores are listed.

As the model configuration was chosen for optimal performance on data set A, it is not surprising that the highest classification score is observed for this data set. Overall, the variation of the classification scores per data set is low, i.e. the models are not biased by the data splitting of the relatively small data sets. High scores are observed for data set B, and significantly lower scores are observed for C and D. The difference in the classification scores reflect the similarity of the brake systems from which the data were acquired. Similar systems exhibit similar scores, i.e. a similar possibility for squeal prediction using the selected deep learning model. The instability conditions for systems C and D are either more complex, or the measurement channels carry less relevant pieces of information such that the classifiers exhibit lower prediction scores compared to systems A and B. Yet, the validation scores clearly indicate the existence of deterministic instability patterns in the load-response behavior of all brake systems. To better understand the emergence of vibrations from an engineering perspective, more insights into the models are required. As a first approach, the sequence-to-sequence classifiers will predict the point of vibration onset, which in turn allows to study the instantaneous loading conditions.
3.5.3. Squeal prediction using a sequence-to-sequence classifier

The second classification task involves more complex models that output a sequence of binary labels indicating the probability of squeal at each time point \( t_i \). Following the hyperparameter study reported in Appendix F, the final model architecture features a single layer of 256 LSTM units, a batch size of 256 and input sequences of 400 samples along time. As longer sequence lengths are required compared to the scalar classification case, one can conclude that longer temporal correlations are playing a role in the squeal prediction. Overall, classification scores

| data set | training set size | validation set size | MCC mean± std |
|----------|-------------------|---------------------|---------------|
| A        | 2827              | 1212                | 0.78 ± 0.02   |
| B        | 2785              | 1195                | 0.75 ± 0.02   |
| C        | 2893              | 1240                | 0.62 ± 0.03   |
| D        | 4536              | 1945                | 0.50 ± 0.06   |

Table 6: Sequence-to-sequence classification result for all data sets using a fixed network configuration. 10 models were fitted per data set, and the average and standard deviation of the validation scores are listed mostly above MCC\( = 0.5 \) are observed in Table 6. Again, the highest scores are obtained for data set A and the deviations introduced by the individual data splitting are small. Also, the two-class behavior between the first family of sets A and B and the second family of sets C and D is observable. For the given model configuration, it seems to be easier to predict the onset and duration of squeal for the first two brake systems.

Direct comparison between the sequence-to-scalar and to-sequence classifiers, that is by means of the actual MCC values, is not possible: while the MCC is computed per observation in the first case, the MCC is computed per time step in the second case. Hence, if the first classifier predicts the emergence of squeal during a braking correctly, high scores can be achieved. On the contrary, the second classifier must additionally predict the onset and duration of squeal correctly, which can lead to lower MCC scores even if the qualitative vibration behavior is captured well. Consider Figure 12 as an example for the sequence-to-sequence classification and the meaning of a particular MCC score value. The graph indicates the practical usage of a sequence-to-sequence classifier that can predict the onset of squeal. A braking from data set A is presented that was not part of the training process, i.e. has not been seen before by the model. Predictions are made for the loading conditions sliced into segments of 400 samples. The fluid and ambient air temperatures as well as the relative air humidity were supplied as additional inputs, but as they are almost constant, they are not displayed here. For this type of drag braking, the disk rotation is kept constant and the pressure is varied. High-intensity squeal at a frequency of 1.8 kHz is excited at \( t \approx 2.0 \) s and remains until the end of the braking. The classifier predicts squeal to set in at \( t = 1.8 \) s and to last to the end of the brake stop. Hence, the overall squeal behavior is very well predicted by the network. The resulting score is 0.85 for this example, which illustrates how strict the MCC penalizes false predictions in the region of squeal onset. Considering the very good approximation of the ground truth label in this case, the MCC scores reported in Table 6 can be considered to represent actually better models than what their actual numerical values propose. The confidence value indicated by the network output from the sigmoid activation is high throughout the complete braking duration. The slicing of the 11 s braking into three segments becomes visible through reduced confidence values at the very beginning of each sequence. In the first epochs of a sequence, the recurrent network has only a short time...
Figure 12: Output of the sequence-to-sequence classification model for a validation sample: left panel displays the loading signals used as input sequences for the model. The top right panel depicts the model prediction as well as the model’s confidence value given by the deviation of the dotted line from the dashed line. The lower right panel shows the spectrogram of the accelerations measured during braking. Overall, the network predicts the onset and duration of the squeal very well. The prediction results in a score of MCC = 0.85 here.

history available for making predictions, such that the classification error can be larger. Overall, it has been shown that squeal is predictable from a rather small set of eight loading conditions using rather simple models trained on rather small data sets. This is a very promising result for both the scientific and the commercial communities involved with disk brake squeal. First, neural network-based analysis and data driven approaches may help to understand the phenomenon better. Second, such models can constitute digital twins for the NVH behavior of brake systems during the engineering design phase, which can help to reduce the amount of hardware testing through faster, less cost-intensive and eco-friendlier virtual development.

3.6. Cross-evaluation

The ultimate objective of most research activities in the field of brake vibrations is to find governing physical principles that explain the driving mechanisms for squeal and its parametric dependencies, i.e. stability boundaries. Theoretically, most of those principles should be independent from a specific system configuration, geometry or component properties. Exemplary, the falling friction slope and the mode coupling instability represent such generic patterns of interest involving bifurcation parameters. To this end, we employ the concept of cross-evaluation to access how well a data-based classifier can predict the vibrational behavior of the present brake system even if the classifier was trained on data stemming from a different brake system.
Such a scenario is natural for systems that are assembled by many components via mechanical joints: it has not only been shown that the joints’ properties are highly variable but also that the joint-induced damping can be significantly larger than material damping [69, 70, 68]. Hence, whenever a system is re-assembled or newly mounted onto a test rig, the dynamics may turn out to be fundamentally different to a previous test.

For the cross-evaluation, each classifier built on an individual data set in Sections 3.5.2 and 3.5.3 is used to predict the squeal behavior of the other three data sets: the classifier $C_A$ built on data set $A$ is used to predict squeal in data sets $B$, $C$ and $D$, and likewise for the other classifiers, without further training. Hence, the classifiers have not seen any data from the different brake systems before. If a classifier built on data set $i$ performs well on data set $j$, we can conclude that the model generalizes well for data sets $i$ and $j$. Hence, the underlying instability regions of brake systems $i$ and $j$ are either very similar, or the classifier may have learned a general physical mechanism that in fact governs brake squeal irrespective of the specific brake system realization.

On the contrary, if poor prediction results are obtained, the instability regimes of brake systems $i$ and $j$ are either very different, or there is not a governing physical instability mechanism that can be read from the available data using the chosen models. As the pairwise data sets $A$, $B$ and $C$, $D$ stem from similar brake systems, those hypothesis can be tested on the data at hand. All data sets are prepared in the same manner, and the classifiers $C_i$ share the same architecture.

The results of this cross-evaluation experiment for the sequence-to-scalar task are depicted in the off-diagonal terms of Table 7. First of all, these classification scores differ significantly from the diagonal and thus represent a degradation of prediction quality when using classifier $C_i$ for predicting squeal in data from system $j$ for $i \neq j$. Then, the scoring matrix is not symmetric such that classifier $C_A$ performs with $\text{MCC} = 0.01$ on data set $B$, but $\text{MCC} > 0.16$ on data set $C$. An interesting observation is that the pairwise similarity of the brake systems that have generated the data can be read from the results of the cross-evaluation. Intra-family scores, e.g. $A$ vs. $B$ and $C$ vs. $D$, are significantly lower than the diagonal entries, but still better than random. Inter-family scores, e.g. $A$ vs. $C$ and so forth, are essentially zero. $\text{MCC}$ scores very close to zero indicate full randomness of the predictions. In a last step, all data are merged to a single set to fit a model on all observations. Trained on 24755 observations and validated against 10613 samples, this model exhibits only poor scores that can be interpreted as some kind of average between the diagonal entries and the off-diagonal entries. The model performs still better than random, but is very unlikely to be used for squeal prediction in its current form.

For the sequence-to-sequence task, the results in Table 8 are qualitatively similar to the previous case. Off-diagonal scores for a data set from a different family of brake systems are very low and essentially indicate that the model prediction is no better than random. For similar brake systems, better scores in the range between $0.37$ to $0.51$ are obtained. Again, we note that the actual value of the $\text{MCC}$ can be misleading here due to its formulation based on each time step. However, there is certainly room for improvement especially for the classifiers $C_C$ and $C_D$.

As a result, we conclude that all of the four brake systems studied in this work exhibit very individual instability regimes in the loading parameter space spanned by the available data. The networks employed here were not able to learn an underlying instability pattern that is invariant to the physical brake system realization. Considering the vast amount of research on brake squeal, its instability mechanisms and parameter sensitivities, this finding is not surprising. However, considering a single brake system, the high prediction quality obtained by LSTM networks is a promising finding. Locally, the instability conditions giving rise to squeal can be learned from rather small data sets in an engineering-compliant fashion, i.e. using data from conventional NVH testing.
This work presents a first proof-of-concept for using data-driven methods and deep learning in brake squeal research. Further studies are required to confirm the findings presented here using four relatively small data sets. As the absolute prediction quality was not in the focus of this work, performance gains are possible when hyperparameters and model architectures are further optimized. Future work will focus on different model architectures. Besides the occurrence of squeal, also the vibration level and the vibration frequency may be interesting squeal characteristics to predict. Furthermore, the limited explainability of deep learning classifiers poses challenges for engineering design decisions. Convolutional networks allow to generate visual indicators, so-called class activation maps, for feature importance. Hence, this is a promising way to obtain higher degrees of explainability which may support the design of new friction materials to reduce squeal. Obviously, larger data sets will help to generalize some of the findings presented in this work.
4. Conclusion

This work proposes to use data-driven analysis approaches for friction-induced vibrations of brake systems. A computer-vision inspired vibration detection and characterization method is discussed in the first part of this work. Shortcomings of state-of-the-art spectral methods are addressed by converting the vibration signals into their visual spectrogram representations. Then, recent deep learning methods from computer vision are trained and employed to distinguish several classes of characteristic vibration phenomena. The comparison to hard-coded spectral algorithms reveals the potential of deep learning approaches for vibration research. While the conventional approach exhibits superior performance in high-frequency squeal detection, the deep learning approaches allow to robustly detect other sounds and overall increase the detection quality for highly automated data processing. In data-intensive vibration research activities this approach represents a flexible, fast and engineering-compliant solution.

The second part of this contribution illustrates how recurrent deep neural networks can be employed to shed light on the instability behavior of brake systems. Experimental data sets comprising several loading conditions as well as the system response are used to generate digital twins for the NVH behavior in a supervised time series classification task. For the first time, it has been shown that the dominant instability regimes are well captured by only few recordings of transient loading conditions. The prediction relies on the historic evolutions of those inputs to learn the vibrational response of the brake system. Not only the emergence of self-excited squeal, but also the time instant of onset can be predicted with appealing quality. Using the chosen model configuration, it does not seem to be advisable to train a single model on multiple measurement data sets stemming from truly different braking systems. Instead, individual classifiers for individual classes of brake systems can be a promising starting point for further research on instability patterns encoded in the loading conditions monitored during NVH testing.

Overall, our findings are promising and may foster new data-driven research on friction-induced dynamics of mechanical structures. For the first time, it is shown how both academia and more applied disciplines can benefit from interdisciplinary approaches of machine learning to brake system vibrations.

Acknowledgment

MS was supported by the German Research Foundation (DFG) within the Priority Program “calm, smooth, smart” under the reference Ho 3851/12-1.

Author contributions

MS, MT and NH designed the research. MS and DSC performed the research and created the artwork. MS, MT and DS wrote the manuscript. NH and SO revised the manuscript.

Appendix A. Confidence scoring for spectral squeal detection

To allow for a consistent comparison to deep learning NVH detectors, we assign confidence values to the conventional spectral detector results. The squeal sound pressure level and the duration are used as proxies to estimate a confidence score. The higher the level, the more confident we are in the detection. Hence, the squeal level in the range of [45, 120] dB(A) is
linearly mapped to the level rating metric $C_1 \in [0, 1]$. Using a histogram of approximately 4000 noisy brakings, we study the distribution of squeal durations $d$ to assign a confidence score $C_2$ based on the duration of the detected event. It turns out that most of the squeals last for 1 to 4 seconds. Owing to its skew shape with single peak, the distribution is approximated by a Gamma probability density function (PDF)

$$y = f(x \mid a, b) = \frac{1}{b^a \Gamma(a)} x^{a-1} e^{-x/b} \quad \text{(A.1)}$$

with shape parameter $a = 2.55$ and scale parameter $b = 1.07$, see Figure A.13(a). The resulting PDF has a maximum value of 0.285 which is used to scale the duration confidence such that $C_2 = f(d \mid a, b) \cdot 0.285 \in [0, 1]$. Now, a final confidence score $C$ is computed

$$C = \frac{C_1 + C_2}{4} + 0.5 \in [0.5, 1] \quad \text{(A.2)}$$

as a linear combination of the level and duration score. Figure A.13(b) displays the confidence score value as a function of squeal duration and squeal level. This confidence score is valid because we do not compare the confidence scores of the spectral and deep learning methods directly. The score is solely required for relative ranking the detections in the process of PRC computation. Hence, the absolute values of this synthetic confidence score are irrelevant.

Figure A.13: Typical distribution of squeal duration (a) fitted by the Gamma probability density function A.1 and overall confidence score A.2 for the spectral detector as a function of squeal duration and squeal sound pressure level

**Appendix B. Object detection metrics**

To evaluate the correct bounding box size and location, the intersection over union (IoU) is computed. The IoU measures the overlap of the ground truth $B_{gt}$ and predicted $B_p$ bounding box as the Jaccard index illustrated in Figure 5:

$$\text{IoU} = \frac{\text{area of overlap}(B_{gt}, B_p)}{\text{area of union}(B_{gt}, B_p)} \quad \text{IoU} \in [0, 1] \quad \text{(B.1)}$$

Taking into account a minimum IoU threshold and bounding boxes of a single class label, the validity of the object detection is defined as follows:

- true positive (TP): $\text{IoU} \geq \text{IoU}_{\text{threshold}}$
• false positive (FP): IoU < \text{IoU}_{\text{threshold}}

• false negative (FN): ground truth objects for which there is no matching detection

There exist no notion of true negatives in object detection as this would correspond to labeling the background with an additional class background. The IoU threshold depends on the specific metric definition and is usually set to \( > 50\% \). Now, each predicted bounding box \( B_p \) can be assigned to TP, FP or FN for each class individually. Typically, for each image the bounding boxes are sorted by their IoU score to cover special cases, such as multiple predictions for a single object. All predicted bounding boxes are listed in a table with their respective validity (TP, FP, FN). As each bounding box prediction features a confidence score, the table can be ranked by this value. Now, the cumulative precision and the recall values can be computed. The precision-recall curve (PRC) illustrates those cumulative measures to evaluate the performance of an object detector for each class separately. Precision, i.e. the positive prediction rate, and recall, i.e. the true positive rate, are contradicting metrics when considering different confidence levels. If the confidence threshold is low, chances are high for over-prediction, i.e. high TP but also high FP rates. If a high confidence level is considered, the number of false negatives will be high. A weak detector has to increase the number of detections to identify all relevant objects, thereby increasing the number of false detections, i.e. the false positives rate. Hence, a good object detector will maintain high precision and recall values for varying confidence scores, thereby finding a maximum of only relevant ground truth objects. This qualitative behaviour can be measured by the area under the curve (AUC) of the PRC. The average precision (AP) \cite{118} measures the mean precision for all recall values. In practise, the PRC is not monotonically decreasing, but has ‘wiggles’ caused by small ranking deviations of the samples, see Figure \ref{fig:precision_recall_curve}. Therefore, the AUC is typically computed by interpolating the PRC. 11-point interpolation segments the recall into 10 equidistant intervals and samples the precision at the maximum precision value per interval, also called \textit{TREC sampling}. In this work we follow the PASCAL VOC definition of the AP \cite{53} which uses all points for an interpolation and estimation of the AUC. Averaging the APs over all classes gives the mean average precision.

Appendix C. Studies on the minimum confidence level

The predictions of the deep learning object detector models come with a confidence score. For building an optimal brake NVH detection algorithm, we have to set a minimum confidence threshold \( C_t \) for reporting predicted objects as brake noise event. A small threshold will create too many false positives, while a too large threshold results in too many false negatives. Figure \ref{fig:confidence_threshold_effect} depicts the class-wise \( F_1 \) score for the classification task and the mean average precision score along increasing minimal confidence thresholds. Different behavior can be observed for the models and individual object classes. To account for imbalanced representation of those classes in typical brake noise tests, we select the optimal confidence threshold such that high scores are achieved for squeal and a good balance is maintained for the remaining classes. Model 3 exhibits poor detection performance for the artefact class and weak performance for the wirebrush class. As a result, the mAP is significantly lower than for the other two models. These detectors show similar behavior for increasing confidence scores: the quality metrics rise for squeal and click sounds while the wirebrush and artefact classes show decreasing detection quality. In the range of \( 0.8 \leq C_t \leq 0.9 \) all \( F_1 \) scores are in the same order of magnitude. Hence, this parameter range is a valid choice for the minimal confidence score required for reporting predicted events when building an optimal brake NVH sound detector.
Figure C.14: Classification quality metric $F_1$ as a function of the minimal confidence score $C$ required for reporting an object in the reference data set and resulting mean average precision mAP. The following thresholds $C_t$ were selected: model 1 $C_t = 0.9$ (mAP = 0.73), model 2 $C_t = 0.84$ (mAP = 0.8) and model 3 $C_t = 0.88$ (mAP = 0.55)

Appendix D. Object detection precision recall curves

Appendix E. Sequence-to-scalar classifiers

Table E.9: Hyperparameter studies for the sequence-to-scalar configuration. Each model was trained for 200 epochs for a 3-fold cross validation on data set $A$. The validation scores are reported by the MCC

| batch size | layers | units | window length | rel. shift size | mean MCC | std MCC |
|------------|--------|-------|---------------|----------------|----------|---------|
| 16         | 1      | 64    | 200           | 0.5            | 0.54     | 0.03    |
| 16         | 1      | 64    | 200           | 0.75           | 0.58     | 0.02    |
| 16         | 1      | 64    | 200           | 1.0            | 0.61     | 0.04    |
| 16         | 1      | 64    | 400           | 0.5            | 0.62     | 0.01    |
| 16         | 1      | 64    | 400           | 0.75           | 0.6      | 0.08    |
| 16         | 1      | 128   | 200           | 0.5            | 0.59     | 0.0     |
| 16         | 1      | 128   | 200           | 0.75           | 0.64     | 0.01    |
| 16         | 1      | 128   | 200           | 1.0            | 0.65     | 0.03    |
| 16         | 1      | 128   | 400           | 0.5            | 0.65     | 0.02    |
| 16         | 1      | 128   | 400           | 0.75           | 0.58     | 0.05    |
| 16         | 1      | 128   | 400           | 1.0            | 0.64     | 0.04    |
| 16         | 1      | 256   | 200           | 0.5            | 0.56     | 0.01    |
| 16         | 1      | 256   | 200           | 0.75           | 0.61     | 0.02    |
| 16         | 1      | 256   | 200           | 1.0            | 0.64     | 0.0     |
| 16         | 1      | 256   | 400           | 0.5            | 0.62     | 0.01    |
| 16         | 1      | 256   | 400           | 0.75           | 0.61     | 0.03    |
| 16         | 1      | 256   | 400           | 1.0            | 0.69     | 0.04    |
| 16         | 2      | 64    | 200           | 0.5            | 0.55     | 0.01    |
| 16 | 2 | 64 | 200 | 0.75 | 0.57 | 0.02 |
| 16 | 2 | 64 | 200 | 1.0  | 0.58 | 0.05 |
| 16 | 2 | 64 | 400 | 0.5  | 0.58 | 0.01 |
| 16 | 2 | 64 | 400 | 0.75 | 0.62 | 0.04 |
| 16 | 2 | 64 | 400 | 1.0  | 0.57 | 0.08 |
| 16 | 2 | 128| 200 | 0.5  | 0.51 | 0.06 |
| 16 | 2 | 128| 200 | 0.75 | 0.58 | 0.02 |
| 16 | 2 | 128| 200 | 1.0  | 0.63 | 0.02 |
| 16 | 2 | 128| 400 | 0.5  | 0.58 | 0.04 |
| 16 | 2 | 128| 400 | 0.75 | 0.62 | 0.04 |
| 16 | 2 | 128| 400 | 1.0  | 0.64 | 0.02 |
| 16 | 2 | 256| 200 | 0.5  | 0.51 | 0.07 |
| 16 | 2 | 256| 200 | 0.75 | 0.58 | 0.02 |
| 16 | 2 | 256| 200 | 1.0  | 0.62 | 0.03 |
| 16 | 2 | 256| 400 | 0.5  | 0.62 | 0.02 |
| 16 | 2 | 256| 400 | 0.75 | 0.6  | 0.03 |
| 16 | 2 | 256| 400 | 1.0  | 0.66 | 0.01 |
| 64 | 1 | 64 | 200 | 0.5  | 0.68 | 0.03 |
| 64 | 1 | 64 | 200 | 0.75 | 0.67 | 0.03 |
| 64 | 1 | 64 | 200 | 1.0  | 0.61 | 0.02 |
| 64 | 1 | 64 | 400 | 0.5  | 0.65 | 0.02 |
| 64 | 1 | 64 | 400 | 0.75 | 0.61 | 0.08 |
| 64 | 1 | 64 | 400 | 1.0  | 0.66 | 0.04 |
| 64 | 1 | 128| 200 | 0.5  | 0.68 | 0.02 |
| 64 | 1 | 128| 200 | 0.75 | 0.7  | 0.02 |
| 64 | 1 | 128| 200 | 1.0  | 0.69 | 0.01 |
| 64 | 1 | 128| 400 | 0.5  | 0.67 | 0.05 |
| 64 | 1 | 128| 400 | 0.75 | 0.62 | 0.09 |
| 64 | 1 | 128| 400 | 1.0  | 0.67 | 0.03 |
| 64 | 1 | 256| 200 | 0.5  | 0.7  | 0.01 |
| 64 | 1 | 256| 200 | 0.75 | 0.69 | 0.01 |
| 64 | 1 | 256| 200 | 1.0  | 0.7  | 0.01 |
| 64 | 1 | 256| 400 | 0.5  | 0.7  | 0.02 |
| 64 | 1 | 256| 400 | 0.75 | 0.71 | 0.02 |
| 64 | 1 | 256| 400 | 1.0  | 0.65 | 0.08 |
| 64 | 2 | 64 | 200 | 0.5  | 0.63 | 0.01 |
| 64 | 2 | 64 | 200 | 0.75 | 0.64 | 0.03 |
| 64 | 2 | 64 | 200 | 1.0  | 0.63 | 0.03 |
| 64 | 2 | 64 | 400 | 0.5  | 0.63 | 0.03 |
| 64 | 2 | 64 | 400 | 0.75 | 0.63 | 0.06 |
| 64 | 2 | 64 | 400 | 1.0  | 0.64 | 0.03 |
| 64 | 2 | 128| 200 | 0.5  | 0.68 | 0.02 |
| 64 | 2 | 128| 200 | 0.75 | 0.71 | 0.02 |
| 64 | 2 | 128| 200 | 1.0  | 0.65 | 0.04 |
| 64 | 2 | 128| 400 | 0.5  | 0.67 | 0.02 |
| 64 | 2 | 128| 400 | 0.75 | 0.63 | 0.03 |
| 64 | 2 | 128| 400 | 1.0  | 0.62 | 0.06 |
| 64 | 2 | 256| 200 | 0.5  | 0.7  | 0.03 |
| 64 | 2 | 256| 200 | 0.75 | 0.69 | 0.02 |
| 64 | 2 | 256| 200 | 1.0  | 0.68 | 0.02 |

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### Appendix F. Sequence-to-sequence classifiers

Table F.10: Hyperparameter studies for the sequence-to-sequence configuration. Each model was trained for 200 epochs for a 3-fold cross validation on data set A. The validation scores are reported by the MCC.

| batch size | layers | units | window length | rel. shift size | mean MCC | std MCC |
|------------|--------|-------|---------------|----------------|----------|---------|
| 16         | 1      | 64    | 200           | 0.5            | 0.56     | 0.01    |
| 16         | 1      | 64    | 200           | 0.75           | 0.67     | 0.04    |
| 64         | 2      | 256   | 400           | 1.0            | 0.66     | 0.04    |
| 256        | 1      | 64    | 200           | 0.5            | 0.7      | 0.01    |
| 256        | 1      | 64    | 200           | 0.75           | 0.71     | 0.03    |
| 256        | 1      | 64    | 200           | 1.0            | 0.65     | 0.05    |
| 256        | 1      | 64    | 400           | 0.5            | 0.68     | 0.0     |
| 256        | 1      | 64    | 400           | 0.75           | 0.65     | 0.06    |
| 256        | 1      | 64    | 400           | 1.0            | 0.65     | 0.02    |
| 256        | 1      | 128   | 200           | 0.5            | 0.68     | 0.01    |
| 256        | 1      | 128   | 200           | 0.75           | 0.73     | 0.02    |
| 256        | 1      | 128   | 400           | 1.0            | 0.69     | 0.03    |
| 256        | 1      | 128   | 400           | 0.5            | 0.66     | 0.01    |
| 256        | 1      | 128   | 400           | 1.0            | 0.69     | 0.05    |
| 256        | 1      | 128   | 200           | 0.5            | 0.73     | 0.01    |
| 256        | 1      | 256   | 200           | 0.75           | 0.74     | 0.01    |
| 256        | 1      | 256   | 200           | 1.0            | 0.72     | 0.01    |
| 256        | 1      | 256   | 400           | 0.5            | 0.72     | 0.02    |
| 256        | 1      | 256   | 400           | 0.75           | 0.74     | 0.02    |
| 256        | 1      | 256   | 400           | 1.0            | 0.73     | 0.04    |
| 256        | 2      | 64    | 200           | 0.5            | 0.65     | 0.02    |
| 256        | 2      | 64    | 200           | 0.75           | 0.71     | 0.02    |
| 256        | 2      | 64    | 200           | 1.0            | 0.66     | 0.02    |
| 256        | 2      | 64    | 400           | 0.5            | 0.69     | 0.02    |
| 256        | 2      | 64    | 400           | 0.75           | 0.66     | 0.01    |
| 256        | 2      | 64    | 400           | 1.0            | 0.65     | 0.01    |
| 256        | 2      | 128   | 200           | 0.5            | 0.68     | 0.02    |
| 256        | 2      | 128   | 200           | 0.75           | 0.7    | 0.03    |
| 256        | 2      | 128   | 200           | 1.0            | 0.69     | 0.04    |
| 256        | 2      | 128   | 400           | 0.5            | 0.71     | 0.01    |
| 256        | 2      | 128   | 400           | 0.75           | 0.74     | 0.03    |
| 256        | 2      | 128   | 400           | 1.0            | 0.65     | 0.05    |
| 256        | 2      | 256   | 200           | 0.5            | 0.69     | 0.01    |
| 256        | 2      | 256   | 200           | 0.75           | 0.71     | 0.01    |
| 256        | 2      | 256   | 200           | 1.0            | 0.7      | 0.02    |
| 256        | 2      | 256   | 400           | 0.5            | 0.72     | 0.02    |
| 256        | 2      | 256   | 400           | 0.75           | 0.73     | 0.04    |
| 256        | 2      | 256   | 400           | 1.0            | 0.68     | 0.03    |
| Layer | Batch Size | Sequence Length | Learning Rate | Loss | Accuracy |
|-------|------------|----------------|--------------|------|----------|
| 16    | 1          | 64             | 1.0          | 0.62 | 0.04     |
| 16    | 1          | 64             | 0.5          | 0.64 | 0.03     |
| 16    | 1          | 64             | 0.75         | 0.64 | 0.03     |
| 16    | 1          | 64             | 1.0          | 0.65 | 0.04     |
| 16    | 1          | 128            | 0.5          | 0.56 | 0.03     |
| 16    | 1          | 128            | 0.75         | 0.61 | 0.01     |
| 16    | 1          | 128            | 1.0          | 0.66 | 0.03     |
| 16    | 1          | 128            | 0.5          | 0.68 | 0.01     |
| 16    | 1          | 128            | 0.75         | 0.67 | 0.03     |
| 16    | 1          | 128            | 1.0          | 0.67 | 0.05     |
| 16    | 1          | 256            | 0.5          | 0.58 | 0.04     |
| 16    | 1          | 256            | 0.75         | 0.61 | 0.02     |
| 16    | 1          | 256            | 1.0          | 0.66 | 0.04     |
| 16    | 1          | 256            | 0.5          | 0.66 | 0.03     |
| 16    | 1          | 256            | 0.75         | 0.69 | 0.01     |
| 16    | 1          | 256            | 1.0          | 0.69 | 0.03     |
| 16    | 2          | 64             | 0.5          | 0.58 | 0.02     |
| 16    | 2          | 64             | 0.75         | 0.62 | 0.02     |
| 16    | 2          | 64             | 1.0          | 0.64 | 0.01     |
| 16    | 2          | 64             | 0.5          | 0.62 | 0.04     |
| 16    | 2          | 64             | 0.75         | 0.67 | 0.03     |
| 16    | 2          | 64             | 1.0          | 0.65 | 0.06     |
| 16    | 2          | 128            | 0.5          | 0.57 | 0.03     |
| 16    | 2          | 128            | 0.75         | 0.62 | 0.01     |
| 16    | 2          | 128            | 1.0          | 0.65 | 0.03     |
| 16    | 2          | 128            | 0.5          | 0.65 | 0.03     |
| 16    | 2          | 128            | 0.75         | 0.67 | 0.0     |
| 16    | 2          | 128            | 1.0          | 0.7   | 0.04     |
| 16    | 2          | 256            | 0.5          | 0.59 | 0.03     |
| 16    | 2          | 256            | 0.75         | 0.62 | 0.03     |
| 16    | 2          | 256            | 1.0          | 0.67 | 0.04     |
| 16    | 2          | 256            | 0.5          | 0.65 | 0.04     |
| 16    | 2          | 256            | 0.75         | 0.69 | 0.03     |
| 16    | 2          | 256            | 1.0          | 0.7   | 0.02     |
| 64    | 1          | 64             | 0.5          | 0.7  | 0.02     |
| 64    | 1          | 64             | 0.75         | 0.68 | 0.04     |
| 64    | 1          | 64             | 1.0          | 0.68 | 0.02     |
| 64    | 1          | 64             | 0.5          | 0.69 | 0.02     |
| 64    | 1          | 64             | 0.75         | 0.71 | 0.01     |
| 64    | 1          | 64             | 1.0          | 0.71 | 0.02     |
| 64    | 1          | 128            | 0.5          | 0.7  | 0.0     |
| 64    | 1          | 128            | 0.75         | 0.7  | 0.01     |
| 64    | 1          | 128            | 1.0          | 0.7  | 0.01     |
| 64    | 1          | 128            | 0.5          | 0.72 | 0.02     |
| 64    | 1          | 128            | 0.75         | 0.71 | 0.02     |
| 64    | 1          | 128            | 1.0          | 0.71 | 0.02     |
| 64    | 1          | 256            | 0.5          | 0.7  | 0.01     |
| 64    | 1          | 256            | 0.75         | 0.72 | 0.02     |
| 64    | 1          | 256            | 1.0          | 0.69 | 0.02     |
| 64    | 1          | 256            | 0.5          | 0.71 | 0.02     |
| Layer Size | Type | Width | Height | Batch Size | Learning Rate | Accuracy | Time | Cost |
|------------|------|-------|-------|------------|---------------|----------|------|------|
| 64         | 1    | 256   | 400   | 0.75       | 0.69          | 0.01     |
| 64         | 1    | 256   | 400   | 1.0        | 0.7           | 0.02     |
| 64         | 2    | 64    | 200   | 0.5        | 0.7           | 0.01     |
| 64         | 2    | 64    | 200   | 0.75       | 0.7           | 0.02     |
| 64         | 2    | 64    | 200   | 1.0        | 0.67          | 0.02     |
| 64         | 2    | 64    | 400   | 0.5        | 0.66          | 0.04     |
| 64         | 2    | 64    | 400   | 0.75       | 0.7           | 0.0      |
| 64         | 2    | 64    | 400   | 1.0        | 0.73          | 0.01     |
| 64         | 2    | 128   | 200   | 0.5        | 0.72          | 0.01     |
| 64         | 2    | 128   | 200   | 0.75       | 0.7           | 0.01     |
| 64         | 2    | 128   | 200   | 1.0        | 0.69          | 0.02     |
| 64         | 2    | 128   | 400   | 0.5        | 0.73          | 0.03     |
| 64         | 2    | 128   | 400   | 0.75       | 0.68          | 0.02     |
| 64         | 2    | 128   | 400   | 1.0        | 0.71          | 0.01     |
| 64         | 2    | 256   | 200   | 0.5        | 0.71          | 0.02     |
| 64         | 2    | 256   | 200   | 0.75       | 0.71          | 0.01     |
| 64         | 2    | 256   | 200   | 1.0        | 0.71          | 0.02     |
| 64         | 2    | 256   | 400   | 0.5        | 0.71          | 0.04     |
| 64         | 2    | 256   | 400   | 0.75       | 0.7           | 0.04     |
| 64         | 2    | 256   | 400   | 1.0        | 0.7            | 0.02     |
| 256        | 1    | 64    | 200   | 0.5        | 0.72          | 0.02     |
| 256        | 1    | 64    | 200   | 0.75       | 0.73          | 0.02     |
| 256        | 1    | 64    | 200   | 1.0        | 0.72          | 0.01     |
| 256        | 1    | 64    | 400   | 0.5        | 0.73          | 0.02     |
| 256        | 1    | 64    | 400   | 0.75       | 0.75          | 0.0      |
| 256        | 1    | 64    | 400   | 1.0        | 0.74          | 0.02     |
| 256        | 1    | 128   | 200   | 0.5        | 0.72          | 0.01     |
| 256        | 1    | 128   | 200   | 0.75       | 0.75          | 0.02     |
| 256        | 1    | 128   | 200   | 1.0        | 0.74          | 0.0      |
| 256        | 1    | 128   | 400   | 0.5        | 0.75          | 0.02     |
| 256        | 1    | 128   | 400   | 0.75       | 0.75          | 0.0      |
| 256        | 1    | 128   | 400   | 1.0        | 0.76          | 0.01     |
| 256        | 1    | 256   | 200   | 0.5        | 0.71          | 0.01     |
| 256        | 1    | 256   | 200   | 0.75       | 0.74          | 0.02     |
| 256        | 1    | 256   | 200   | 1.0        | 0.74          | 0.01     |
| 256        | 1    | 256   | 400   | 0.5        | 0.76          | 0.0      |
| 256        | 1    | 256   | 400   | 0.75       | 0.77          | 0.001    |
| 256        | 1    | 256   | 400   | 1.0        | 0.77          | 0.0      |
| 256        | 2    | 64    | 200   | 0.5        | 0.72          | 0.01     |
| 256        | 2    | 64    | 200   | 0.75       | 0.73          | 0.0      |
| 256        | 2    | 64    | 200   | 1.0        | 0.73          | 0.0      |
| 256        | 2    | 64    | 400   | 0.5        | 0.74          | 0.01     |
| 256        | 2    | 64    | 400   | 0.75       | 0.72          | 0.03     |
| 256        | 2    | 64    | 400   | 1.0        | 0.75          | 0.01     |
| 256        | 2    | 128   | 200   | 0.5        | 0.71          | 0.01     |
| 256        | 2    | 128   | 200   | 0.75       | 0.74          | 0.03     |
| 256        | 2    | 128   | 200   | 1.0        | 0.73          | 0.01     |
| 256        | 2    | 128   | 400   | 0.5        | 0.74          | 0.02     |
| 256        | 2    | 128   | 400   | 0.75       | 0.75          | 0.0      |
| 256        | 2    | 128   | 400   | 1.0        | 0.74          | 0.01     |
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Figure D.15: Precision recall curves for the object detection task using a IoU threshold of 50%

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Figure E.16: Training history of the sequence-to-scalar classifiers using the final model configuration and a stratified 70 – 30 training-validation data split. Overfitting cannot be observed until 500 training epochs. The classification score saturates for classifiers A, B and C while some performance gains can be expected for classifier D when trained for more epochs.

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