Detecting and identifying brake noises from a vehicle is crucial at all stages of its lifetime, from the earliest stages of development to years after a customer purchased it. Disturbing noises are responsible for 360k warranty cases for BMW Group (2018), and concerns 14% of the manpower with a high level of expertise. Developing methods for automatic identification that enable faster and more accurate diagnostic would lead to high savings in manpower, increased customer satisfaction and less warranty cases.

Key methods used: Convolutional Neural Network, Recurrent Neural Network, Object detection, Sound Similarity Analysis Conducted for Unlabeled Data

- BMW Group is building a noise database (potentially unlabeled) containing different car noises and the associated repair
- Successful identification of noises similar to each other would enable engineers to quickly refer to repairs conducted before

Challenges in the Dataset

- Lack of Samples
- Imbalanced Data (6 classes)
- Background Noises

Class Specific Data Augmentation

- No brake noise: 29% 
- Lift-groan: 7% 
- Creep-groan: 12% 
- Squeal: 25% 
- Disc-crackle: 23% 
- Horn-groan: 4%

Noise Filtering – 3 Methods

- Amplify brake noise
- Remove various background noises (eg. engine, microphone)

1. Nearest Neighbor Filter
2. Spectral Gate Filter
3. Microphone Noise Filter

Moving from Classification to Detection

- Adapted Single Shot Multibox Detector (SSD) for noise detection
- Enables automatic noise cutout

- Identify Closest Neighbor
- Calculate Distance between Noises
- Cutting out the noise
- Dynamic Time Warping

Deep Learning Models

- Convolutional Neural Network
- Long Short-Term Memory
- Ensemble Model: CNN + LSTM

Feature Extraction

- Spectrogram
- Spectral Feature (spectral roll-off)
- Spectral Feature (spectral flatness)

Test Vehicles

- Identify issues during development
- Decrease warranty cases on long term
- Collect more data and reduce the number of tests / number of vehicles needed during development

Car Sharing Vehicles

- Optimize the vehicle service intervals with predictive maintenance
- Raise customer driving experience

Customer Vehicles

- Provide the right solution rapidly
- Increase customer satisfaction and reduce warranty costs

Test Vehicles

- Identify Closest Neighbor
- Distance between Noises
- Cutting out the noise

1080 Audio Samples (recorded on test cars)

1. Data Processing
2. Noise Classification
3. Noise Detection and More
4. Business Impact

Improved Accuracy and Recall

- Accuracy improved: 80.4% → 90%

Prediction App Deployed in AWS

- Sensor Data: Audio Samples
- 60% Test and 40% Training
- Classifiers trained: CNN + LSTM
- Ensemble model: CNN + LSTM + Multinomial Logistic Regression
- Train on “Train_1 + Train_2” and test on “Test”
- Test case: “Train_1 + Train_2” sound examples
- Confidence prediction: 0.90, 0.80, 0.70, 0.60, 0.50, 0.40, 0.30, 0.20, 0.10, 0.00
- Machine learning model prediction: Disc-crackle: 0.90, Squeal: 0.80, Lift-groan: 0.70, Creep-groan: 0.60, Horn-groan: 0.50, Overall: 0.40

Sound Similarity Analysis Conducted for Unlabeled Data

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Human Expertise VS Automated Classification

- BMW Group: MIT MBAn 2020 Faculty Advisor: BMW Group, Munich