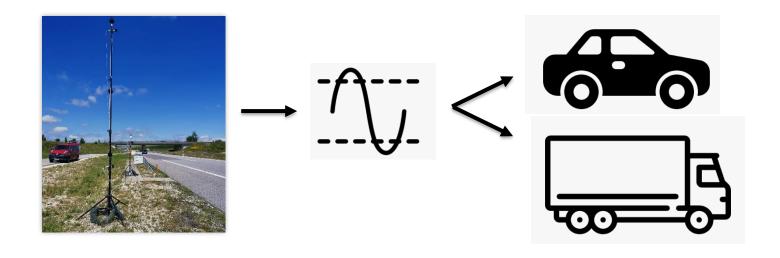
# Determining the Noise Behaviour of the German Vehicle Fleet by Measurement

# Project of the Federal Department of Environment

Determine the **noise behaviour** of the german vehicle fleet by making measurments in **30** different locations



**Project aim:** develop a classification method for passenger cars and heavy vehicles in order to distinguish them

#### **Timeline**

- Kick-Off
- Introduction to problem
- Project management
- Data processing: analyze data distribution & use different data features
- Machine Learning: try different models

Day 1 - 08/01

#### Day 2 - 09/01

- Continue with data processing
- Machine Learning: build one big model
- Continue with data processing
- Model training
- · Model testing
- Perfomance analysis
- Look into futher approaches
- Reflection meeting

Day 3 - 10/01

#### Day 4 - 11/01

- Look deeper into futher approaches
- Analyse results
- Documentation

- Presentation
- Poster creation

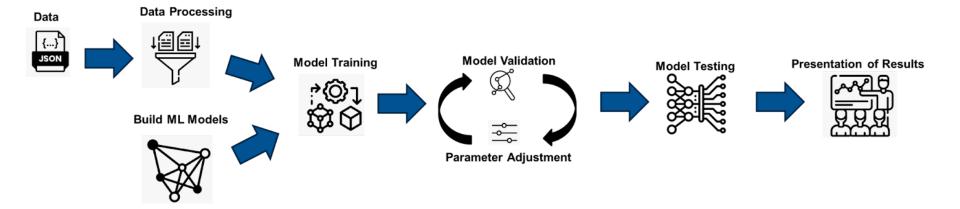
Day 5 - 12/01







# **Problem Approach**





# **Captured Data**

'ID':	unique ID
'MP':	measurement location number
'IDMP':	measurement location specific ID
'timestamp':	time stamp
'Lmax1':	max sound pressure level (SPL) channel 1
'Lmax2':	max SPL channel 2
'Lmax3':	max SPL channel 3
'levelTime1':	level-time-curve channel 1
'levelTime2':	level-time-curve channel 2
'levelTime3':	level-time-curve channel 3
'prominencel':	peak prominence of level-time-curve channel 1
'prominence2':	peak prominence of level-time-curve channel 2
'prominence3':	peak prominence of level-time-curve channel 3
'width1':	peak width of level-time-curve channel 1
'width2':	peak width of level-time-curve channel 2
'width3':	peak width of level-time-curve channel 3
'T6_1':	T6 time channel 1
'T6_2':	T6 time channel 2

```
'Leq1':
                     equivalent SPL channel 1
'Leq2':
                     equivalent SPL channel 2
'SEL1':
                     sound exposure level channel 1
'SEL2':
                     sound exposure level channel 2
'thirdSpectrum1':
                     third-octave band spectrum channel 1
'thirdSpectrum2':
                     third-octave band spectrum channel 2
'thirdSpectrum3':
                     third-octave band spectrum channel 3
'trajectory':
                     passby localization angle over time
'distance':
                     distance between vehicle and microphone
'temperature':
                     air temperature
'relativeHumidity':
                     air humidity
'windSpeed':
                     wind speed
'velocity':
                     vehicle speed
                     vehicle length (estimated by radar)
'radarPulses':
'timeGap':
                     time to previous vehicle
'vehicleClass':
                     vehicle category
```



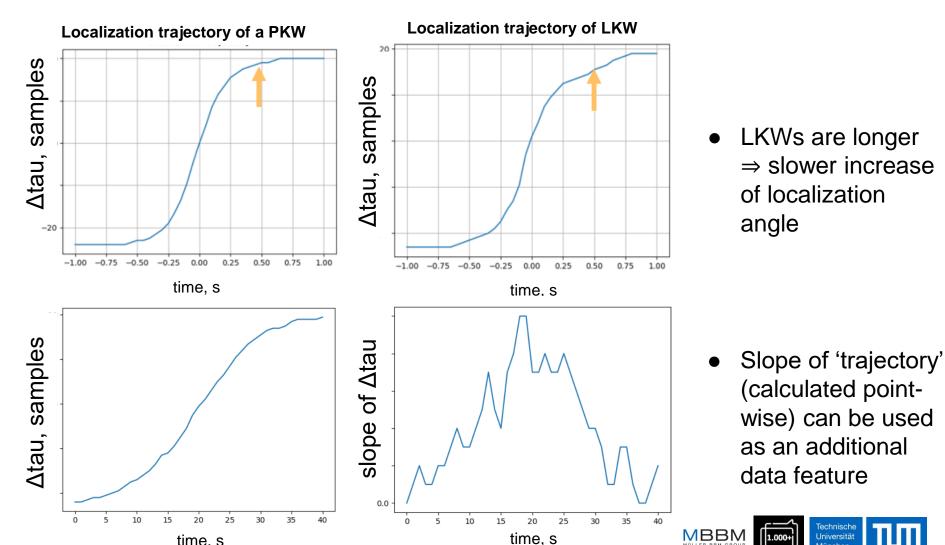
## **Captured Data - Examples**

# Level of the pass-by Third spectrum Localization trajectory Solution in the pass-by and the

- 'Lmax': max sound pressure level (max in 'levelTime' curve)
  - T 6: width of the peak in 'levelTime' curve at (Lmax 6) dB
- 'thirdSpectrum': third-octave spectrum measured at a short time interval around the time point of max sound level
- 'trajectory': measure of vehicle localization (angle between mic pair axis and direction of sound)

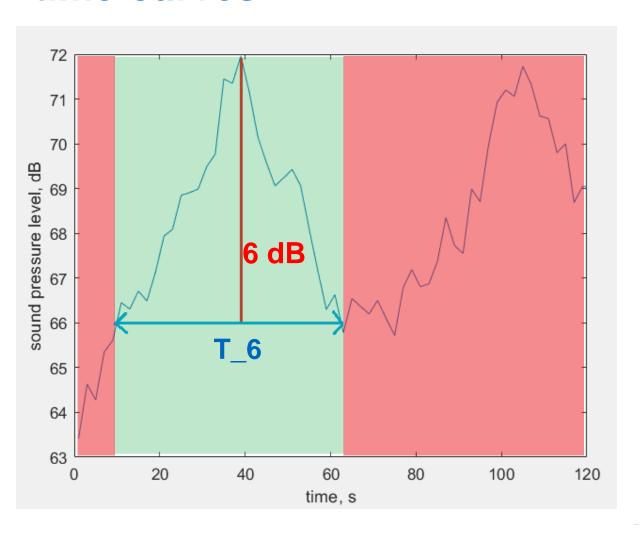


# Data Processing – Slope of trajectory as an additional data feature



time, s

# Data Processing – Filtering out noise in leveltime-curves

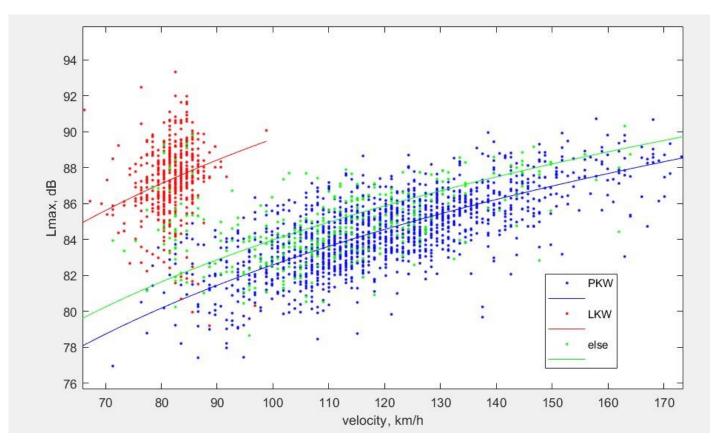


- Cropping 'levelTime' data at T\_6 interval can help to get rid of noise produced by non-target cars in audio recordings
- Should be handled carefully in case of closely following cars (the peaks might not be resolved with 6 dB criterion)





# Data Processing – Deleting data features by normalization



- Max sound pressure level (Lmax) linearly increases with Ig(velocity)
- The feature 'velocity' can be discarded if the Lmax values are normalized by Ig(velocity)

Scatter plots of Lmax vs. velocity and respective regression curves

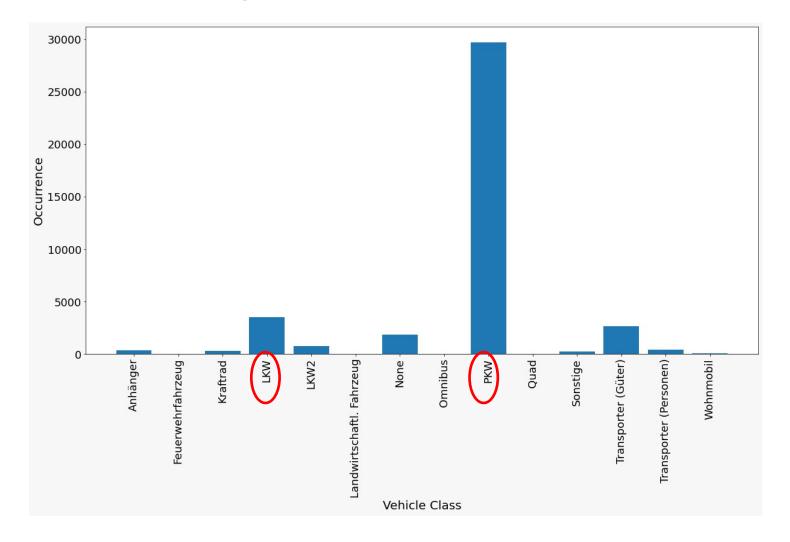








#### **Data: Vehicle Class Distribution**





# **Data Processing: Filter Features**







'ID'

**df:** all datapoints, **all features** (40114 x **34**)

**filtered\_df:** all datapoints, **suggested features** (40114 x 9)

```
'MP'
'Lmax1'
'levelTime1
'T6_1'
'thirdSpectrum1'
'trajectory'
'radarPulses'
```

'vehicleClass'

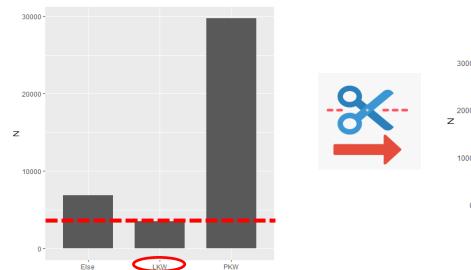
# **Data Processing: Adjust Class Distribution**

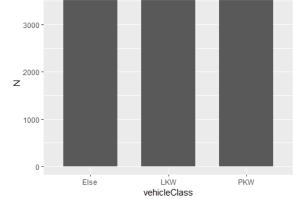
#### Shuffel data table



ID	MP	Lmax1	levelTime1	T6_1	thirdSpectrum1	trajectory	radarPulses	vehicleClass
1384	MP2	0,00909	[61.68, 62.05,	1,9	[32.82, 44.63, 36.6	[-20.0, -19.0	822	LKW
3942	MP4	0,00844	[64.0, 64.22, 6	2,9	[31.4, 24.98, 30.28	[-20.0, -20.0	412	PKW
39678	MP29	0,01015	[70.915, 71.49	1,3	[34.38, 42.45, 43.5	[-1.0, -5.5, -	374	PKW

#### **Extract equal datapoints for each class**





filtered\_final\_df: datapoints with equal ratio 'Else': 'LKW': 'PKW' (10563x9)

Distribution over all locations of **filtered\_df** (**40114** x 9)







# **Data Processing: Normalize Data**

#### **Normalization**

Single values: find min and max values in column, normalize values as

 $new_x = (x-min)/(max-min)$ 

Arrays: divide each value in every array with the max value found in the column

#### Remove locations with special conditions

Location	Condition
MP 30, MP 5	Road surface
MP 12, MP 13	Winter



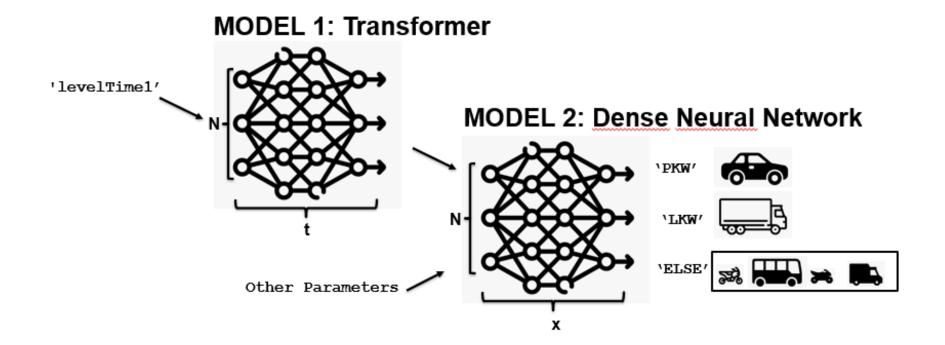
# **Data Processing: Datasets**

Color code: designed, created, used

Name	Description	Size	
ID1	all datapoints, all features	29882 x 34	
ID2	all datapoints, selected features	39676 x 9	
ID3	all datapoints, all features, 3 classes		
ID4	all datapoints, selected features, 3 vehicle classes		
ID5	all features, 3 equally distributed vehicle classes		
ID6	selected features, 3 equally distributed vehicle classes		
ID7	all features, 3 equally distributed classes, special locations in bottom rows		
ID8	selected features, 3 equally distributed vehicle classes, special locations in bottom rows		
ID9	selected features, 3 equally distributed vehicle classes, special locations excluded	9873 x 9	
ID10	selected features, 3 equally distributed vehicle classes, additional features		

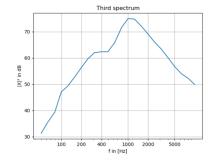


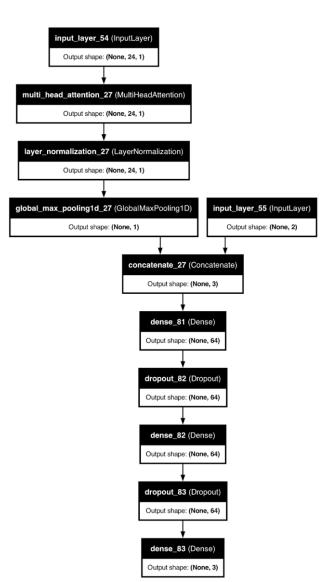
# **Machine Learning Model**

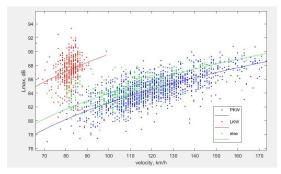




# **Machine Learning Model**

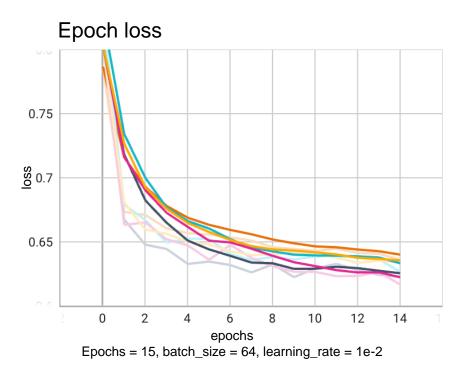




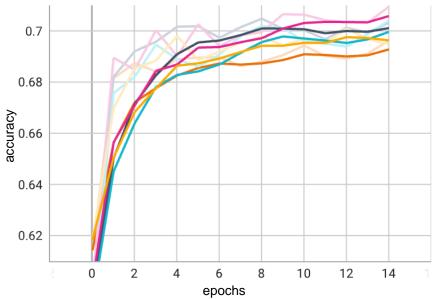




# **Model Testing**



#### **Epoch accuracy**



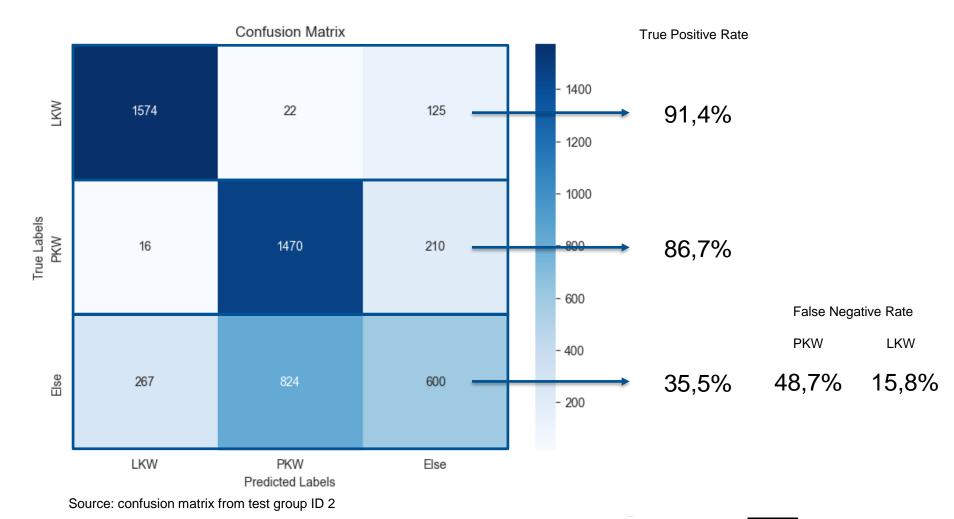
Epochs = 15, batch\_size = 64, learning\_rate = 1e-2



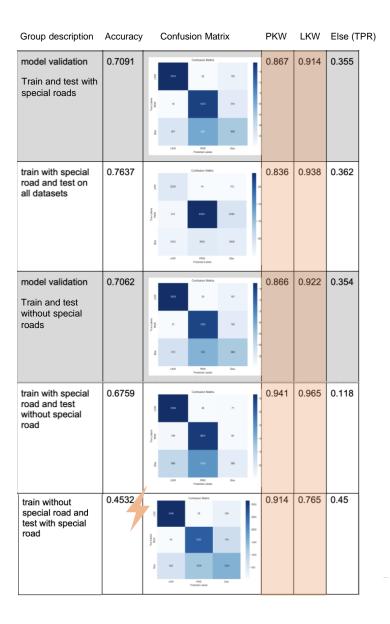




## **Test Accuracy**



#### Results



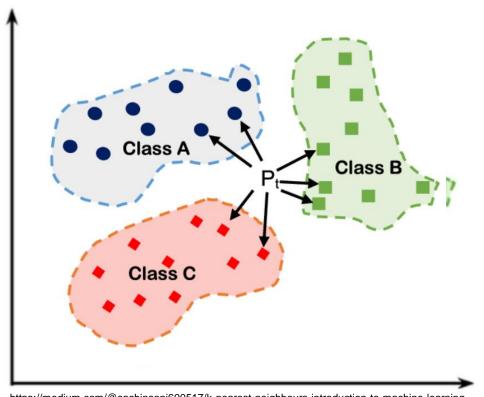


#### Results

- a robust classification between LKW (trucks) and PKW (cars) based on the given datasets.
- There is a noticeable limitation when identifying the 'Else' group, evidenced by its lower true positive rate.
- The model trained with data on special roads performs well on datasets, but reversely it doesn't. It is suggested using the dataset with the special road for the training process

# **Conventional Machine Learning Model**

# K Nearest Neighbors(KNN)



https://medium.com/@sachinsoni600517/k-nearest-neighbours-introduction-to-machine-learning-algorithms-9dbc9d9fb3b2

#### **Three Classes:**

PKW; LWK; Else

#### Input:

float array

#### **Output:**

classification index





# **Testing Results**

Training size	Dataset	lnnut	Acquiracy		c	onfusion Matrix		
Training size	Dalasel	Input	Accuracy	9 - 6	35	1760	283	- 10000
				ů.				- 8000
		levelTime1,	all: 0.81524	rue Labels PRW -	38	10880	35	- 6000
(23243, 188)	ID4_normalized. csv	trajectory, thirdSpectrum1	LKW: 0.81905 PKW: 0.94997	,				- 4000
	<b>03</b> ¥	T6_1,	Else: 0.23712	NO - 2	02	45	1118	- 2000
		Lmax1, RadarPulse		E	se	PKW Predicted Labels	LKW	
		levelTime1, trajectory, thirdSpectrum1	all: 0.69073 LKW: 0.91007			Confusion Matrix		- 1200
(6130, 188)	ID6_normalized.			WON -	1265	8	117	- 1000
•				ue Labeis PKW	22	979	356	- 800 - 600
three classes equally distributed	CSV	T6_1, Lmax1,	PKW: 0.72144 Else: 0.43209	Ē				- 400
equally distributed		RadarPulse		를 -	217	544	579	- 200
					LKW	PKW Predicted Labels	Else	
		levelTime1,				Confusion Matrix		
(=== (		trajectory,	all: 0.70075	w.		14	114	- 1000
(5794, 188) remove special location	ID9_normalized. csv	thirdSpectrum1 T6_1,	LKW: 0.90214 PKW: 0.74240 Else: 0.45900	si s				- 800
		Lmax1,		True Labels PKW	20	928	302	- 600
		RadarPulse		9g -	224	482		- 200
					uśw	PKW	Else	
			_	<u>.</u> =	<u></u>	Predicted Labels Technische	77 27	

# **Testing Results**

Training size	Dataset	Input	Accuracy		Confusion Matrix		
				M) - 1268	14	108	- 1200 - 1000
(6130, 24)	ID6_normalized. csv	thirdSpectrum1	all: 0.69195 LKW: 0.91223 PKW: 0.67797	True Labels PKW - 52	920	412	- 800
			Else: 0.47761	중 - 232	468	640	- 400 - 200
		lovelTime4		uów	PKW Predicted Labels  Confusion Matrix	Else	- 1200
(6130, 188)	ID6_normalized.	levelTime1, trajectory, thirdSpectrum1	all: 0.69073 LKW: 0.91007	WH - 1265		117	- 1000 - 800
three classes equally distributed	CSV	T6_1, Lmax1, RadarPulse	PKW: 0.72144 Else: 0.43209	True Labels PKW N	979	356	- 600 - 400
				∰ - 217 LKW	544 PKW Predicted Labels	579 Else	- 200
(2043, 188)			all: 0.67813		Confusion Matrix		2500
reduced training	ID6_normalized.	_	LKW: 0.90214 PKW: 0.74240	MX- 250	27	267	- 2000 - 1500
size			Else: 0.45900 all: 0.69814	True Label PKW 45	1950	679	- 1000
(8173, 188) increase training size	ID6_normalized. csv	_	LKW: 0.91079 PKW: 0.73252	∰ - 428 UKW		1092 Else	- 500
			Else: 0.45152  MBBM MÜLLER-BBM GROUP	1.000+	Technische Universität München	ПЛ	

#### Results II

- Commendable performance with a small dataset. As the volume of data increases, the model shows a slight improvement
- The model is good at distinguishing between 'PKW' and 'LKW' categories. However, its ability to differentiate the 'else' category is relatively weak
- The 'thirdSpectrum' feature plays a crucial role in enhancing the model's performance

#### **Final Results**

- 2 Machine Learning approaches to classify the vehicles
- Different Data Processing steps to improve classification process
- Improvement of softskills
- Poster with overview of project week

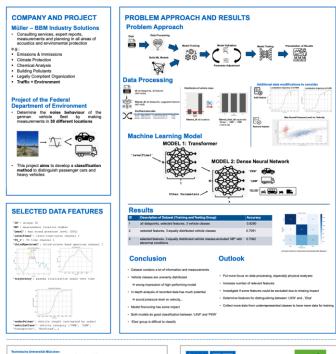
Technische Universität München



#### Determining the Noise Behaviour of the German Vehicle Fleet by Measurement

Müller-BBM Industry Solutions GmbH - Project of the Federal Department of Environment

Lingfeng Gu, Xiaoheng Hu, Aleksandra Kolbasnikova, Nolwen Prat, Nathalie Schneider, Alemsah Tanriverdi















#### Conclusion

- Dataset contains a lot of information and measurements
- Vehicle classes are unevenly distributed
  - → wrong impression of high performing model
- In depth analysis of recorded data has much potential (sound pressure level vs velocity,..)
- Model fine-tuning has some impact
- Both models do good classification between 'LKW' and 'PKW'
- 'Else' group is difficult to classify



#### **Outlook**

- Put more focus on data processing, especially physical analyses
- Increase number of relevant features
- Investigate if some features could be excluded due to missing impact
- Determine features for distinguishing between 'LKW' and ,Else'
- Collect more data from underrepresented classes to have more data for training