TECHNISCHE UNIVERSITÄT DRESDEN

P2O Process2Order

DRESDEN concept

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Deep Learning for Computer Vision in Process Industry

KEEN Abschlusskonferenz

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KEEN

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Outline

Problem Definition

Deep Learning

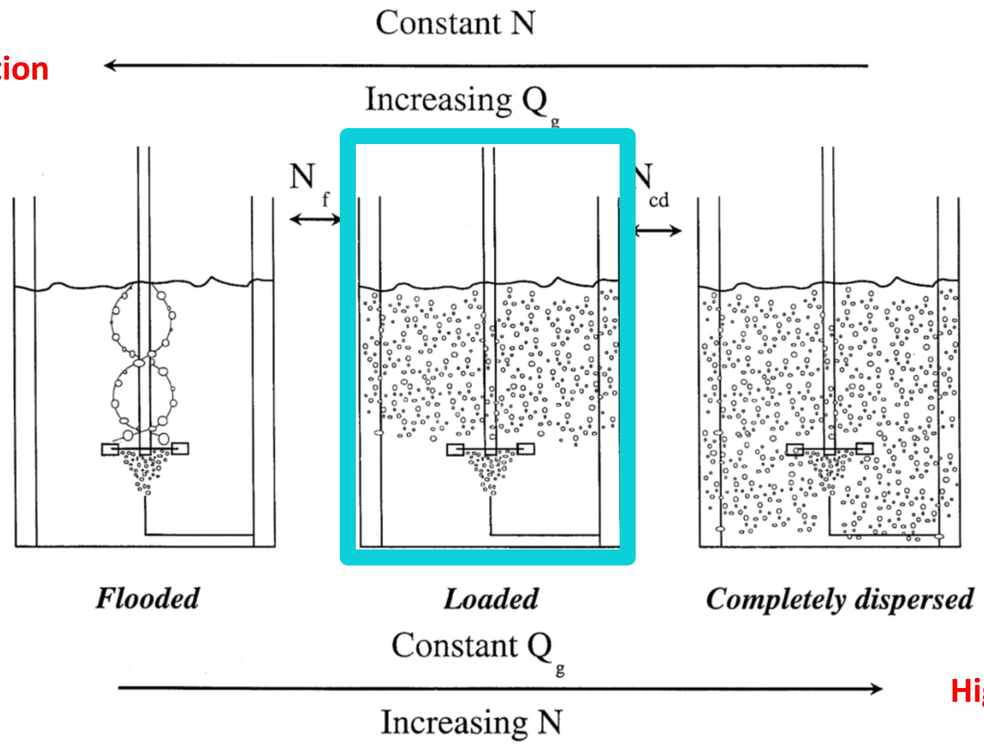
Deep Transfer Learning

Multimodal Modelling

Sensor Deployment

Aeration Process in Stirred Tanks

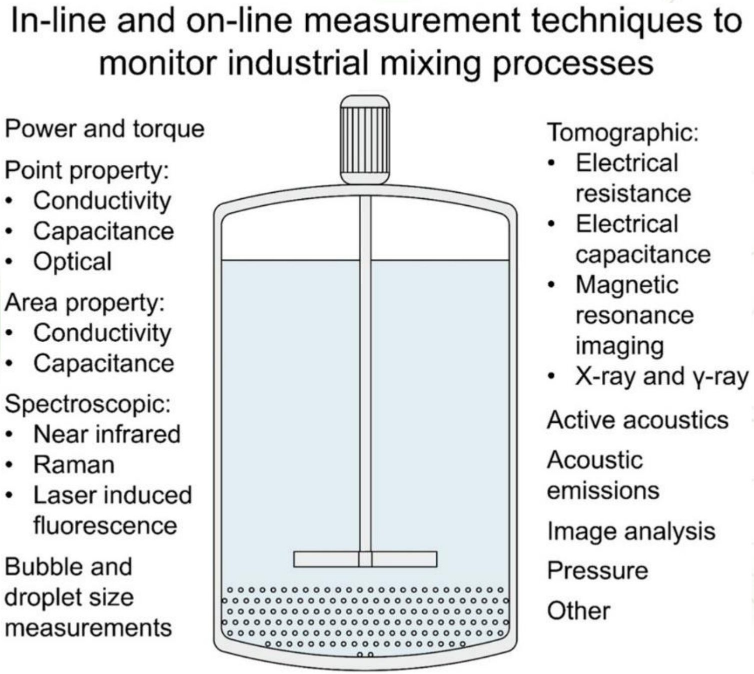
Higher Gas Consumption



Higher Energy Consumption

(Paglianti et al., 2000)

Aeration Process in Stirred Tanks



(Bowler et al., 2020)

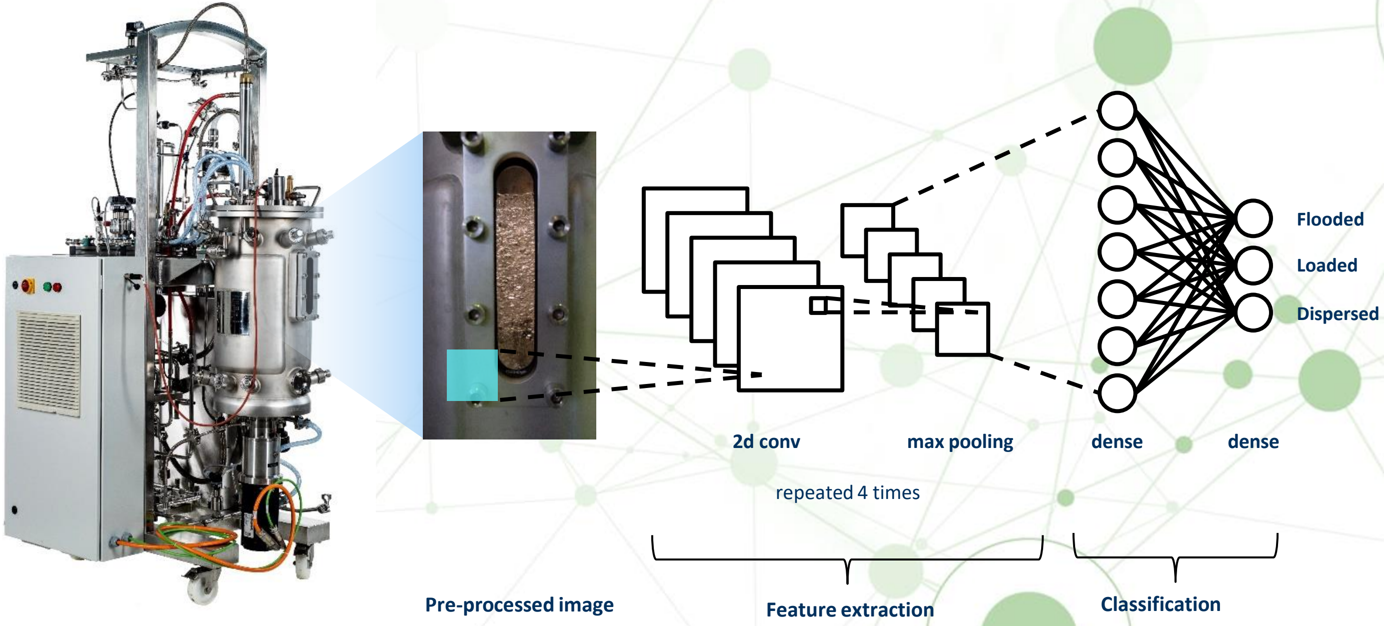
Selected approaches for flow regime identification:

- Static flow map (Nienow, 1985)
- Probe-based conductance fluctuations (Pagliatini et al., 2000)
- Torque and pressure data analysis (Khopkar et al., 2005)
- Single-point optical probe using Machine Learning for classification (Manjrekar et al., 2019)
- Single-point pressure sensors with Deep Learning for classification (Khan et al., 2022)

Dependency on substance properties

Deep Learning for Flow Regime Classification

Hypothesis: visual information is enough to reliably detect flow regimes in bioreactors

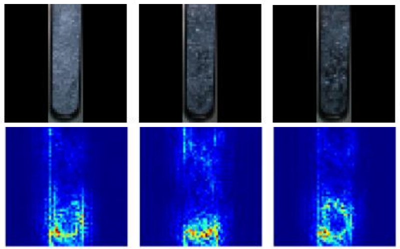


Lenet-5 (Accuracy = 0.96)

		Actual		
		Flooded	Loaded	Dispersed
Predicted	Flooded	316	0	0
	Loaded	0	308	23
	Dispersed	0	15	313

Class Activation Map

Dispersed | Loaded | Flooded



(Kröger, 2021) and (Kröger et al., 2022)

Transfer Learning

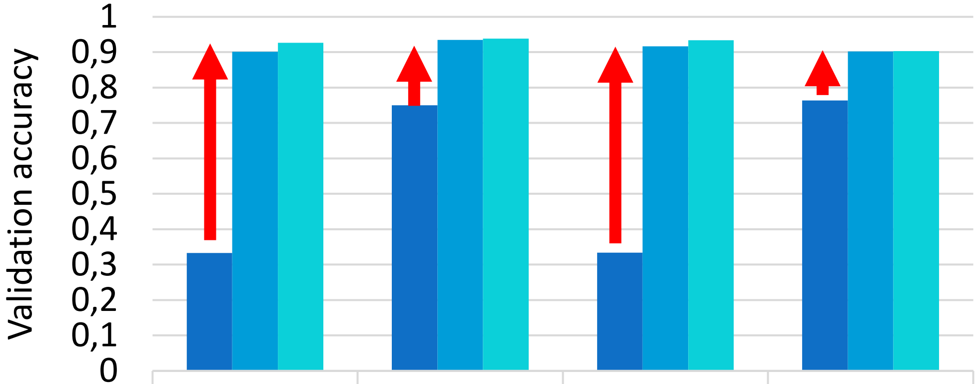
Hypothesis: pre-trained model and using transfer learning techniques can result in better classification results compared to training models from scratch

Tested models (pretrained on ImageNet1K1V):

- AlexNet (57 Mio parameters)
- VGG16 (134 Mio parameters)
- ResNet50 (24 Mio parameters)
- DenseNet121 (26 Mio parameters)

For comparison:

- Linear regression (6 parameters)
- LeNet-5 (60k parameters)

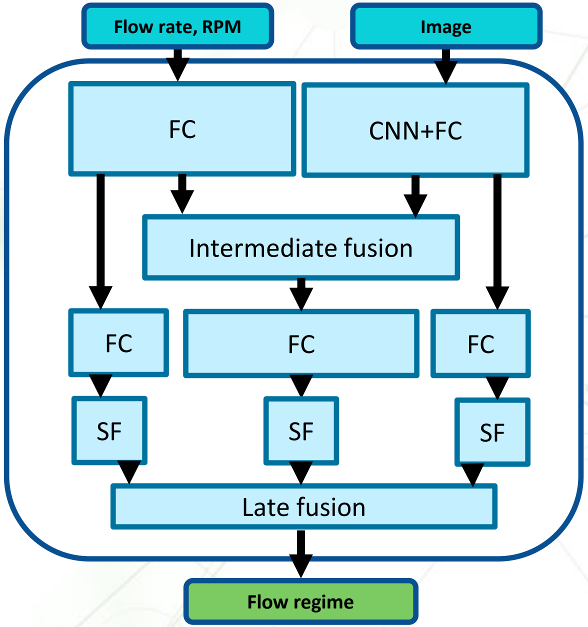


	AlexNet	ResNet50	VGG16	DenseNet
none	0,333	0,750	0,333	0,764
full	0,901	0,934	0,917	0,902
2-step	0,927	0,938	0,934	0,903

(Marc Philipp Becker, 2022) and (Khaydarov et al., 2023)

Multimodal Modelling

Hypothesis: adding process values as an additional modality can increase the overall model`s classification performance



Feature extraction from images

Feature learning

Classification

FC - fully connected layer
CNN - convolutional layer
SF - softmax function

Unimodal – Lenet5 (Accuracy = 0.94)

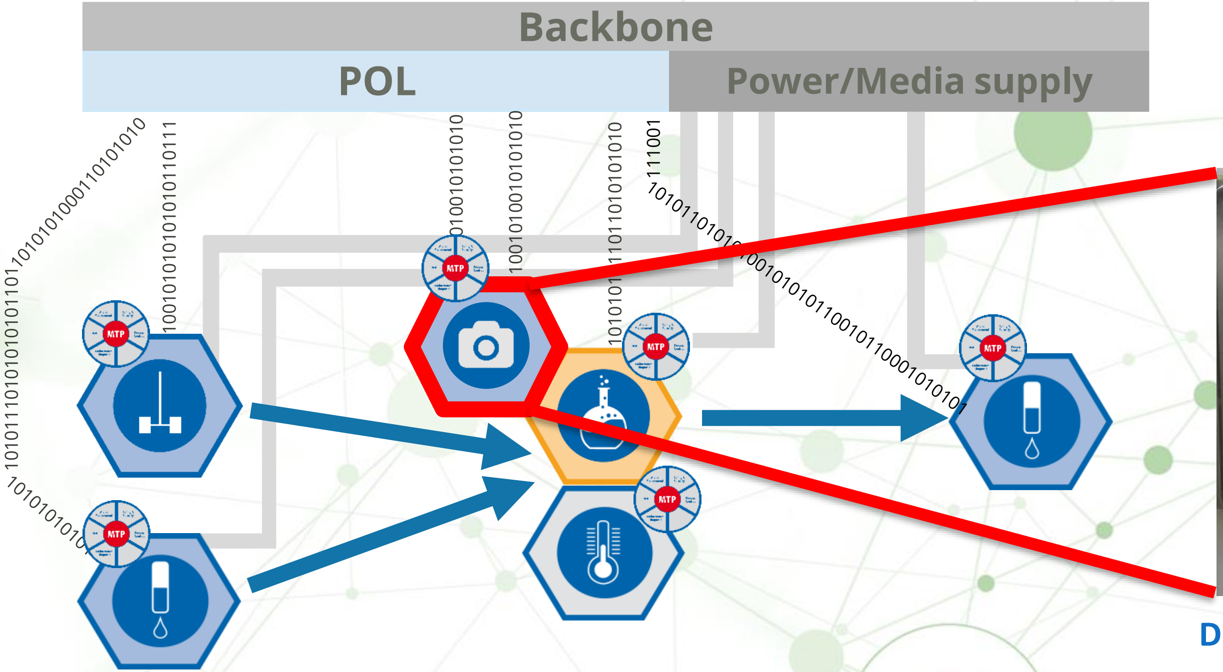
		Actual		
		Flooded	**Loaded**	**Dispersed**
Predicted	**Flooded**	759	31	12
	Loaded	30	1324	85
	Dispersed	5	68	1292

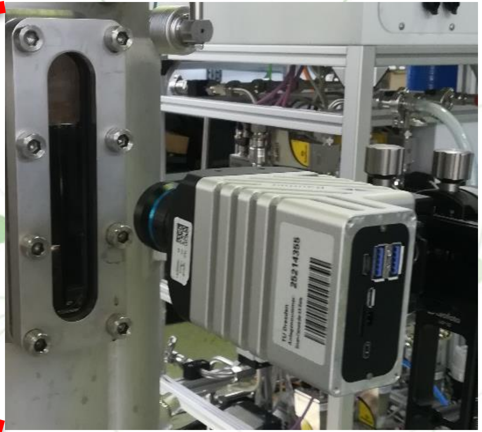
Multimodal, hybrid fusion (Accuracy = 0.99)

		Actual		
		Flooded	**Loaded**	**Dispersed**
Predicted	**Flooded**	799	1	2
	Loaded	1	1429	9
	Dispersed	6	6	1353

(Markus Esser, 2022)

Sensor Deployment



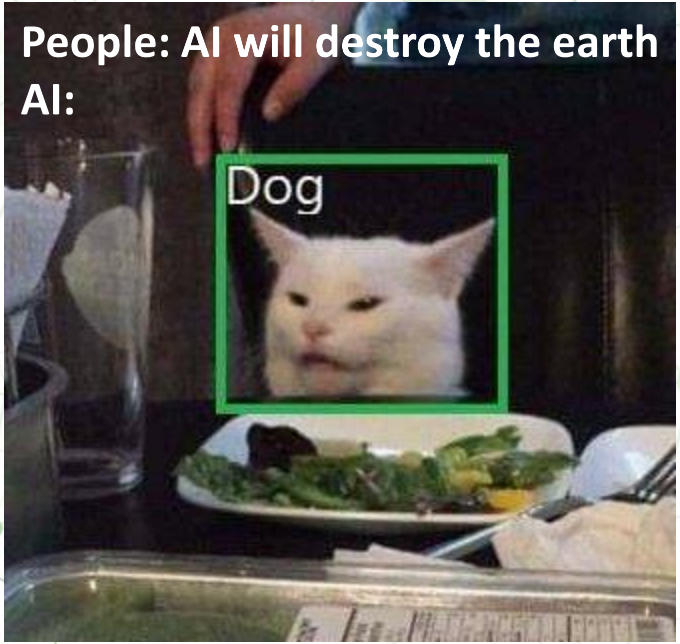


Deployment on Edge using MTPPy

(Valentin Khaydarov et al., 2022) and (Laura Neuendorf et al., 2023)

Summary

- Deep Learning provides a powerful tool for Computer Vision applications in the Process Industries
- Pre-trained models and Deep Transfer Learning has a positive effect for the considered application
- Adding further modalities to the model as features increases its performance
- Visual soft sensors can be deployed using Module Type Package



Thank you for your attention!

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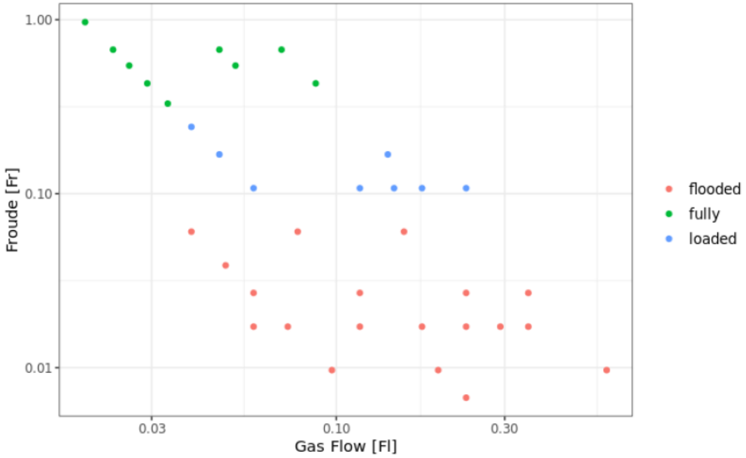
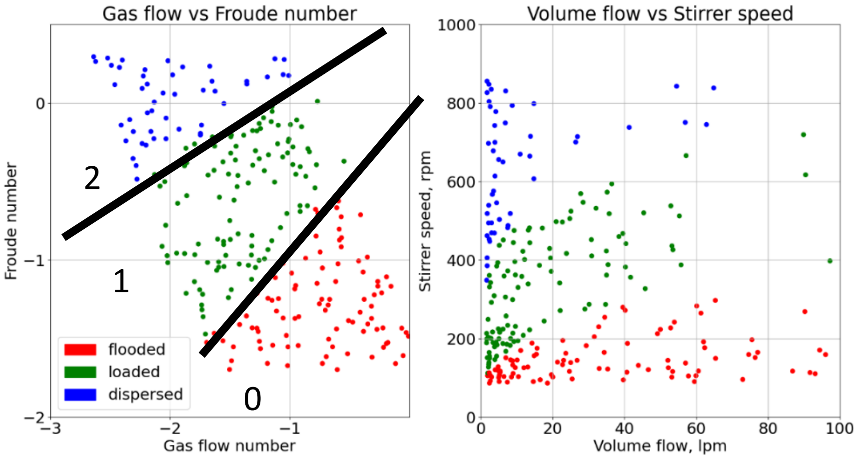
Enhanced Data Collection

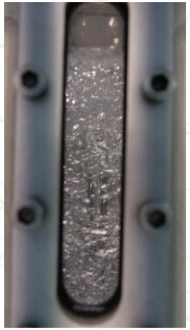
- Even random distribution of samples
- Fully automated recipe execution and data acquisition

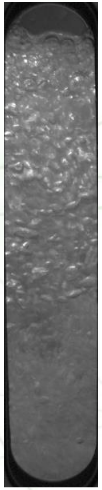




Experimental Setup

- Industrial-grade smart camera Baumer VAX-50C.I.NVX (2/3" sensor, low shutter speed)
- Ultra wide angle 6mm lens Kowa LM6HC
- Light shielding using a black cloth
- Precise and repeatable camera positioning using a robot arm and ARUCO markers (in progress)



Study on Effect of Camera Position

Hypothesis: camera position has a significant impact on the model`s classification performance

Left Radial Position (Accuracy = 0.84)

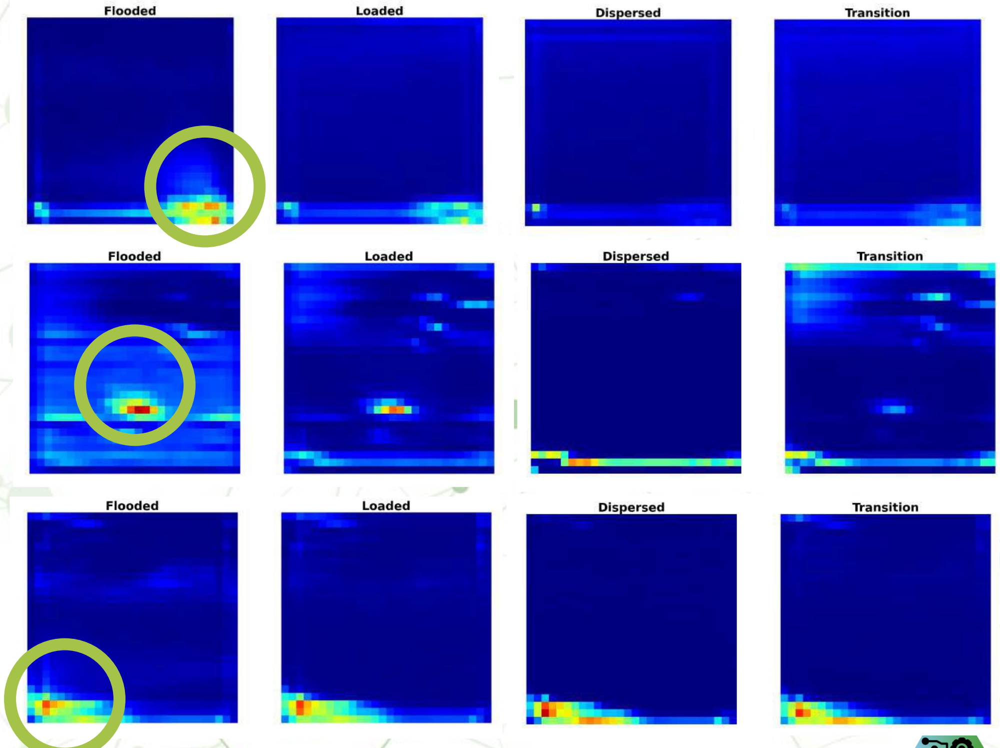
		Actual			
		Flooded	Loaded	Transition	Dispersed
Predicted	Flooded	1070	149	5	0
	Loaded	173	947	145	1
	Transition	0	152	1015	51
	Dispersed	0	0	130	1082

Central Radial Position (Accuracy = 0.96)

		Actual			
		Flooded	Loaded	Transition	Dispersed
Predicted	Flooded	1130	60	1	0
	Loaded	113	1156	10	0
	Transition	0	6	1252	0
	Dispersed	0	0	2	1215

Right Radial Position (Accuracy = 0.94)

		Actual			
		Flooded	Loaded	Transition	Dispersed
Predicted	Flooded	1111	102	2	0
	Loaded	62	1157	31	0
	Transition	1	75	1173	0
	Dispersed	0	0	20	1196



(Leonard-Riccardo Hans Wecke, 2022)