

Deep Learning in the Wild

***8th IAPR TC3 Workshop on Artificial Neural Networks in
Pattern Recognition, September 19-21, 2018, Siena, Italy***

*T. Stadelmann, M. Amirian, I. Arabaci, M. Arnold, G. F. Duivesteijn, I. Elezi,
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Research type A and B



Research type A and B



Motivated by general progress

- Given *known environment*
(learning target, data, evaluation metric)

→ Goal: *fundamental advance in method*

Research type A and B



Motivated by application

- Facing *unclear/unprecedented learning target & data quality / quantity* issues

→ Goal: new *product* & advance in method

Motivated by general progress

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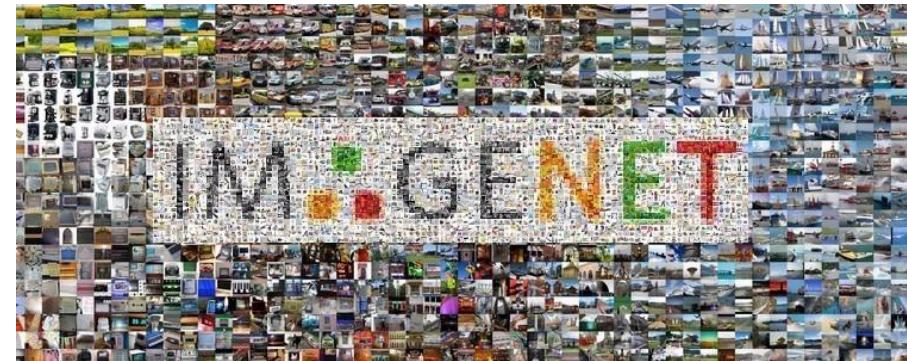
Research type A and B



Motivated by application

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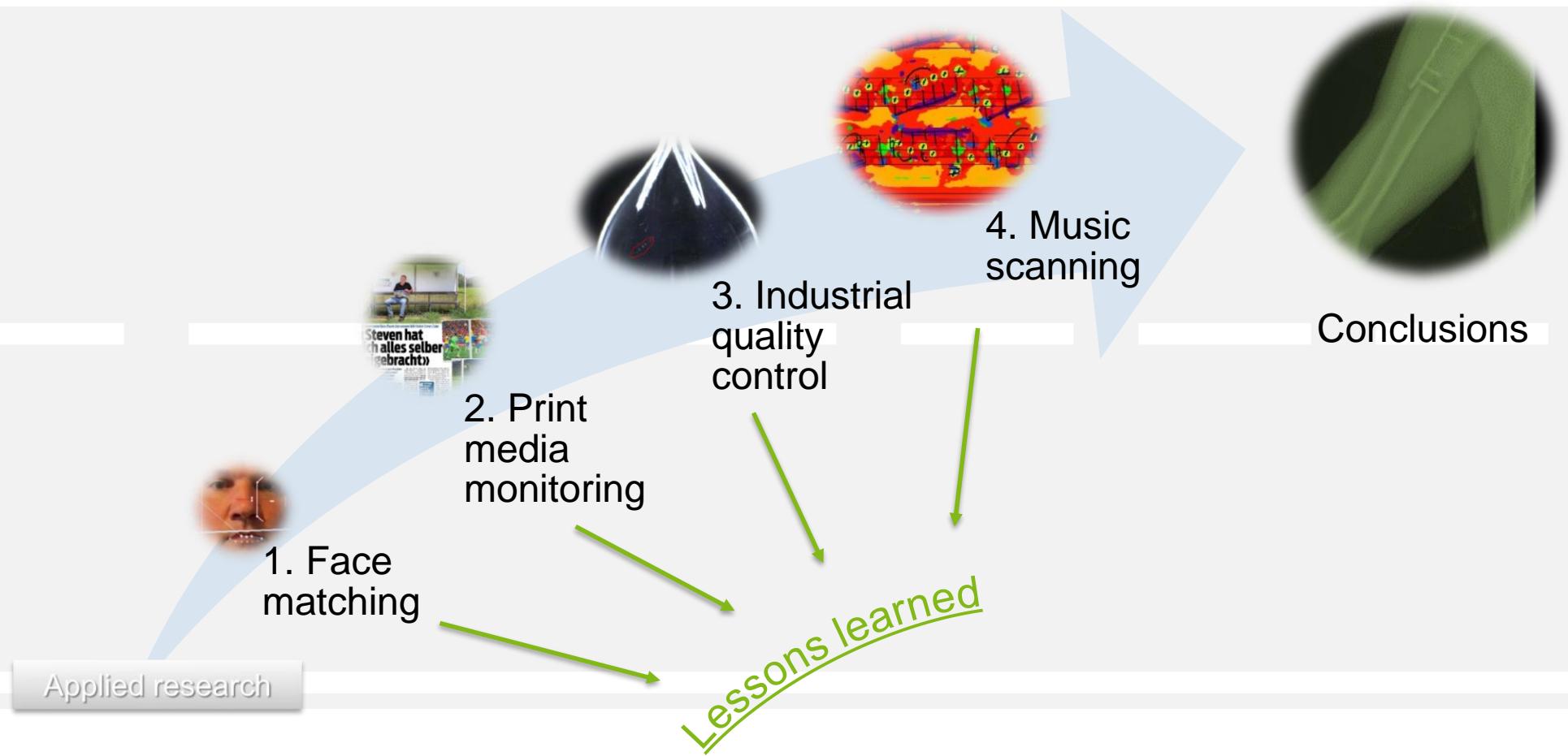
Motivated by general progress

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Roadmap



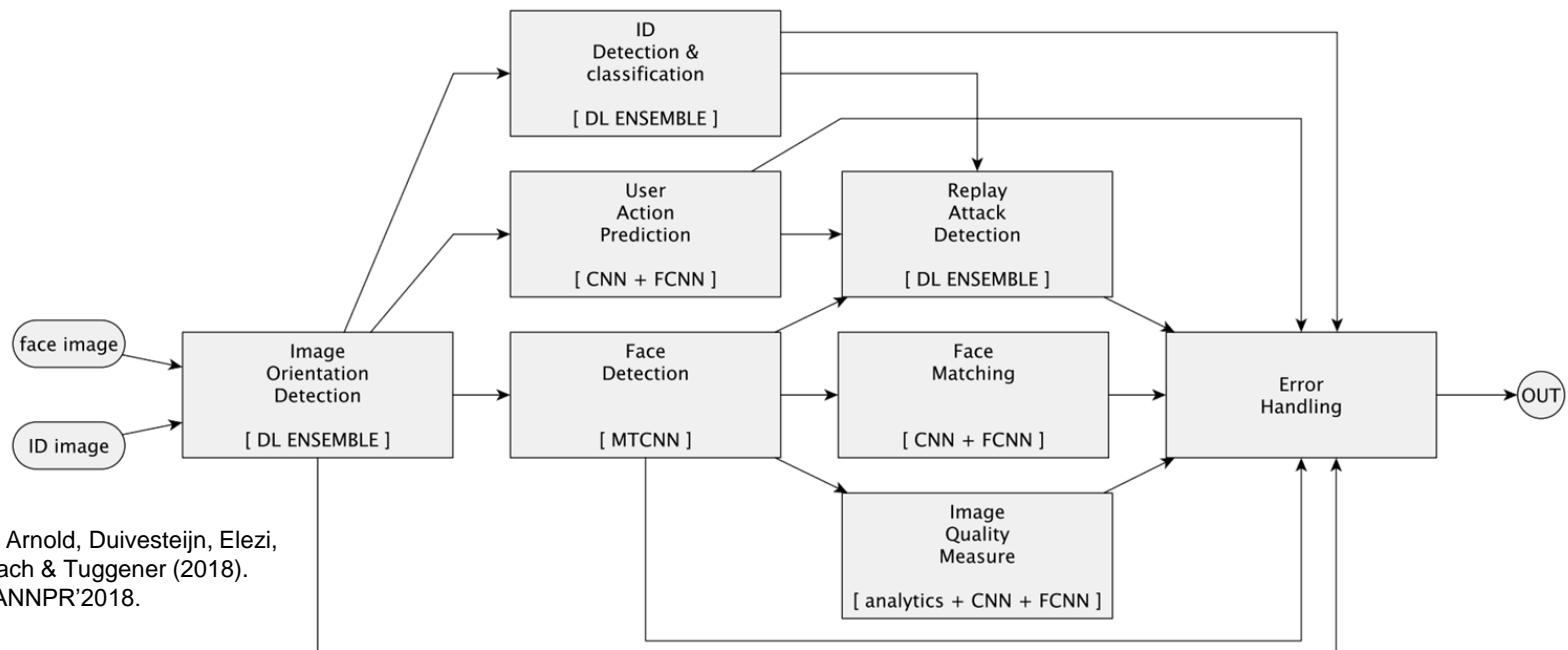
1. Face matching



DEEPIMPACT

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1. Face matching – challenges & solutions



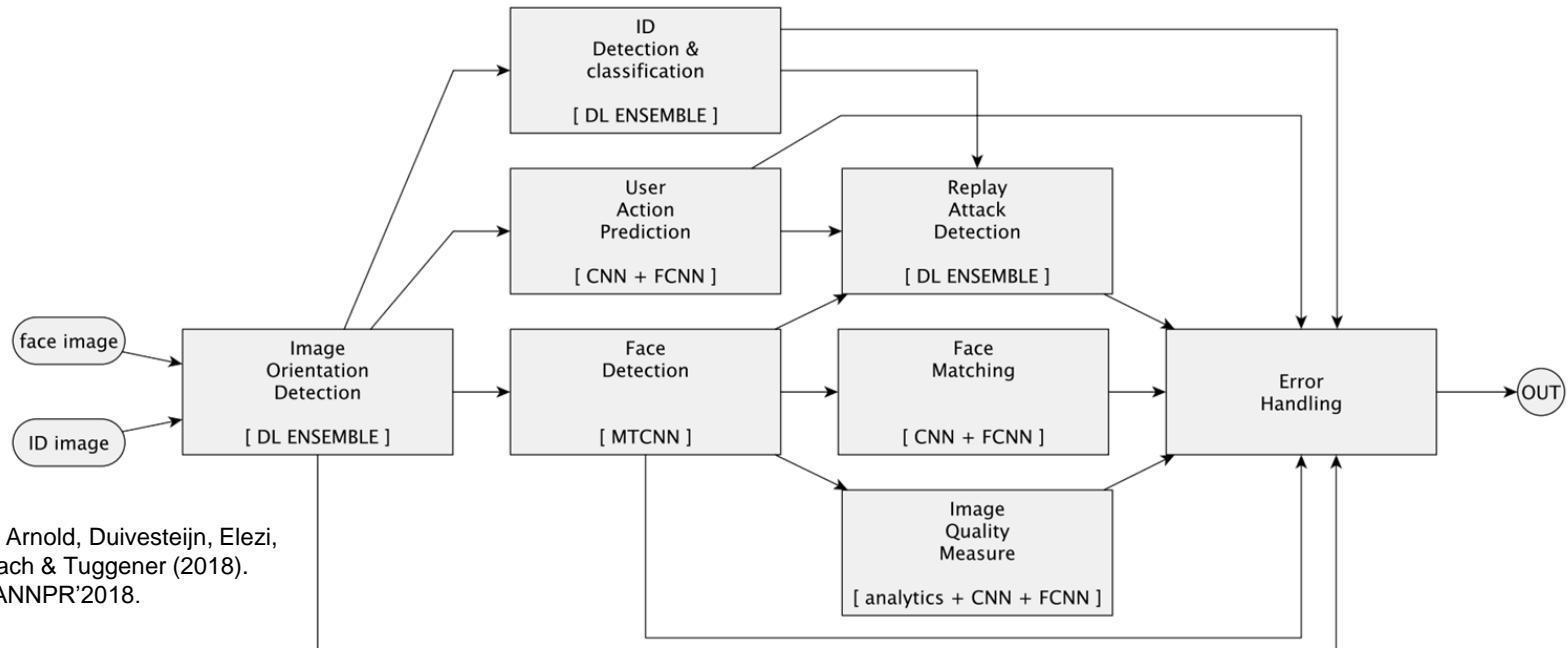
Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi,
Geiger, Lörwald, Meier, Rombach & Tuggener (2018).
«Deep Learning in the Wild». ANNPR'2018.

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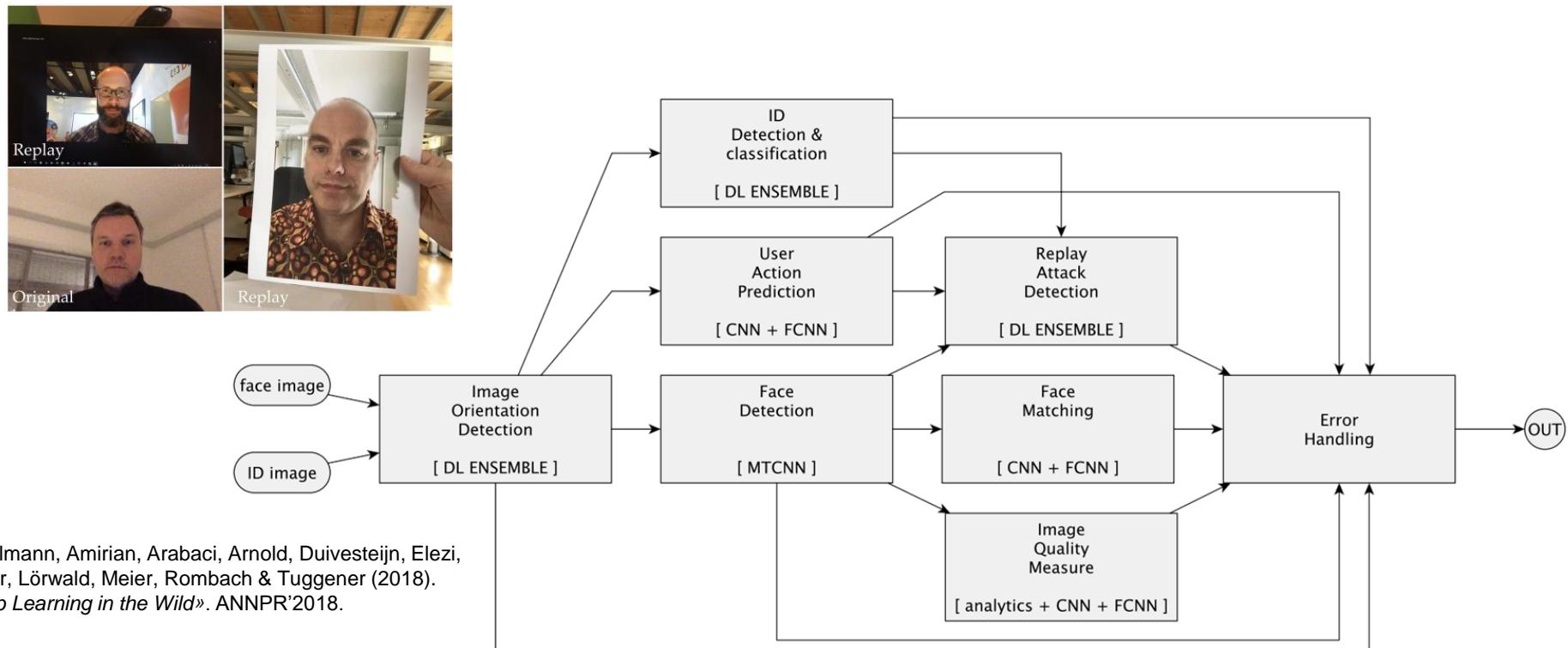
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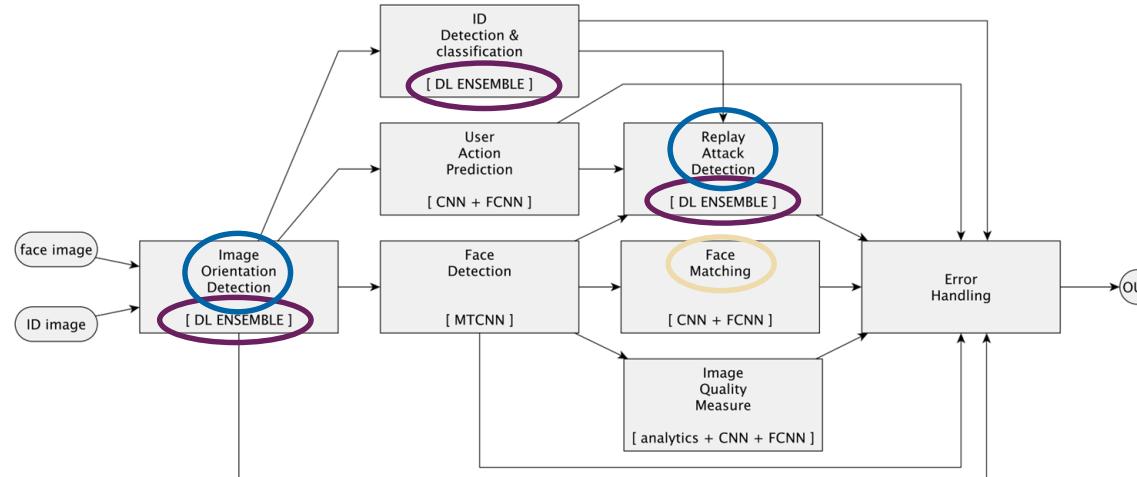
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Lessons learned 1/4



Deployment

- Might involve the buildup of up to dozens of **other machine learning** models to flank the **original core part**.



- Specialized models** for identifiable sub-problems increase the accuracy in production systems over all-in-one solutions, and **ensembles** of experts help where no single method reaches adequate performance.

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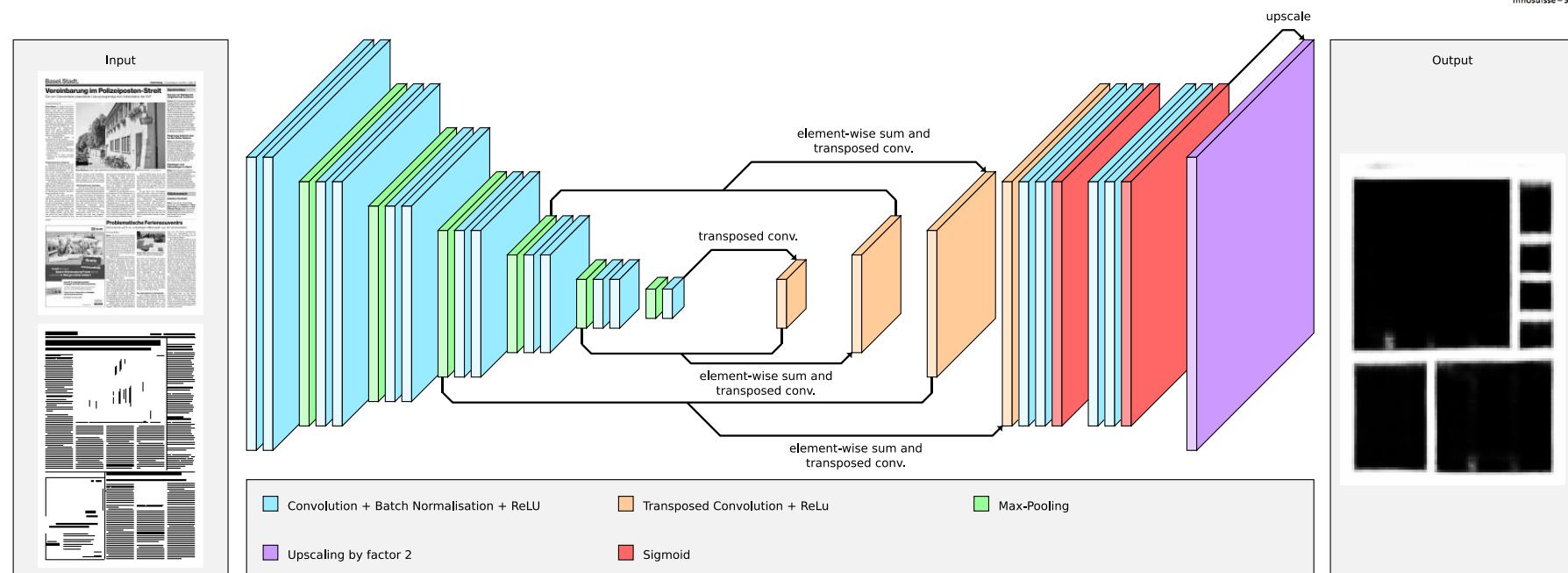
2. Print media monitoring

Task

Challenge

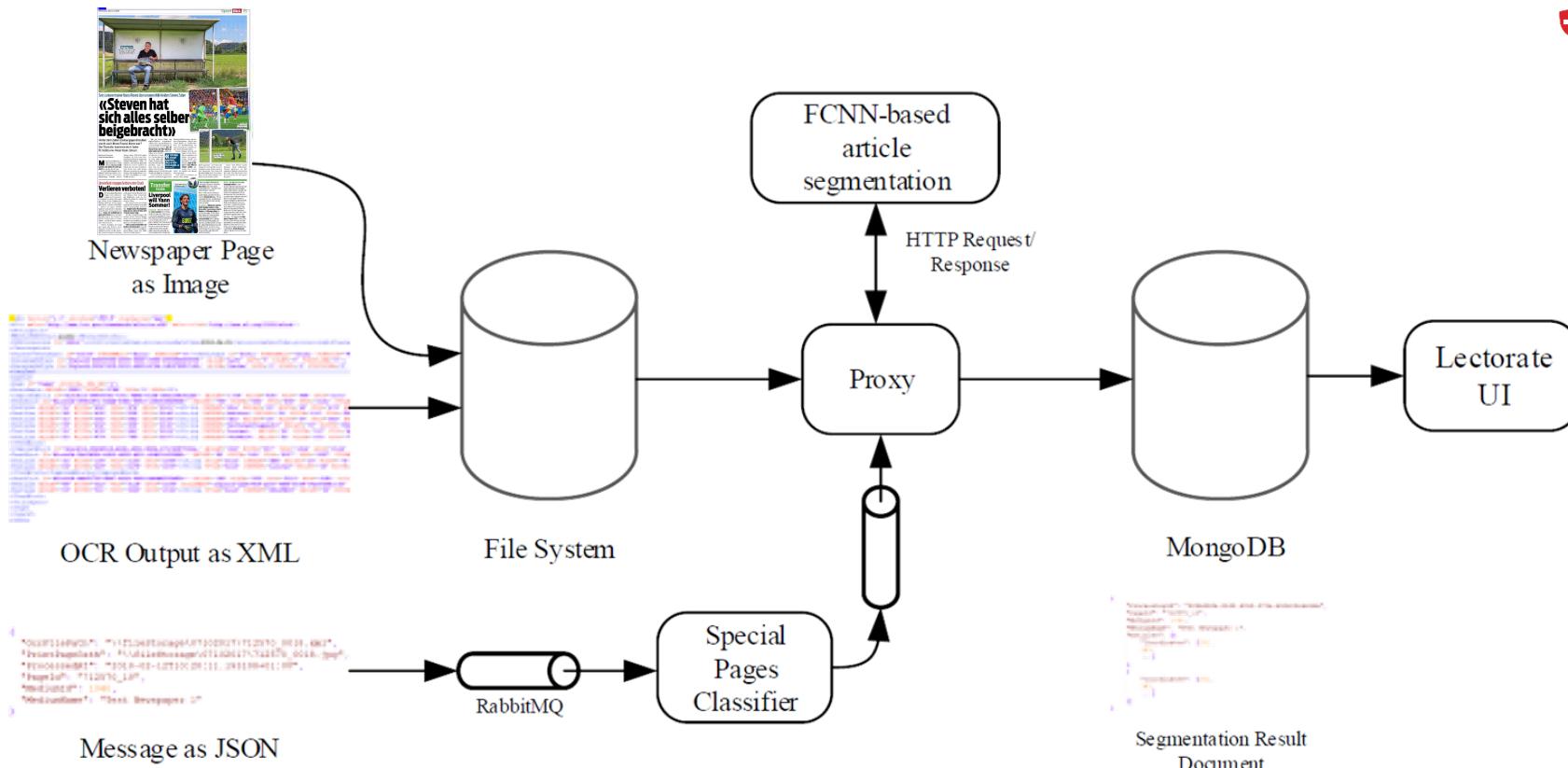
Nuisance

2. Print media monitoring – ML solution



Meier, Stadelmann, Stampfli, Arnold & Cieliebak (2017). «*Fully Convolutional Neural Networks for Newspaper Article Segmentation*». ICDAR'2017.
 Stadelmann, Tolkachev, Sick, Stampfli & Dürr (2018). «*Beyond ImageNet - Deep Learning in Industrial Practice*». In: Braschler et al., «*Applied Data Science*», Springer.

2. Print media monitoring – deployment



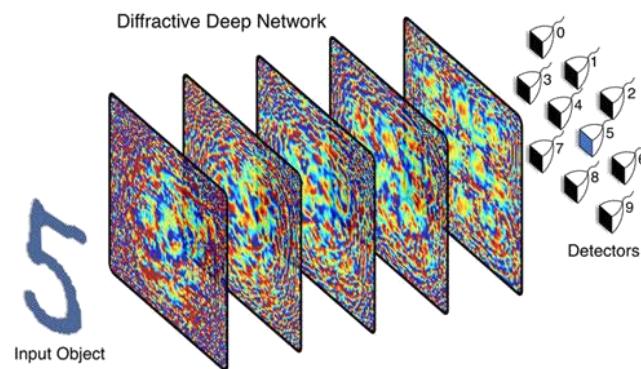
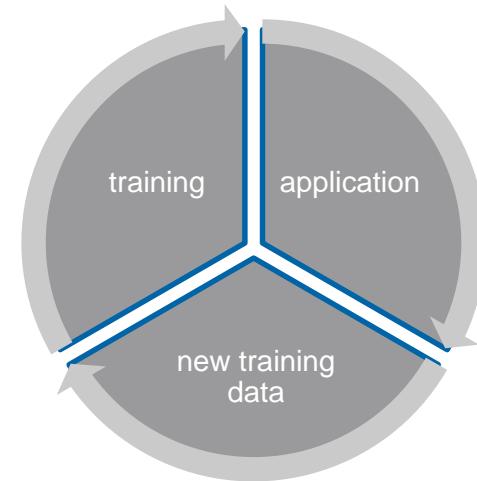
Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörväld, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

Lessons learned 2/4



Deployment

- Should include **continuous learning**
- Needs to take care of **processing speed / efficiency**

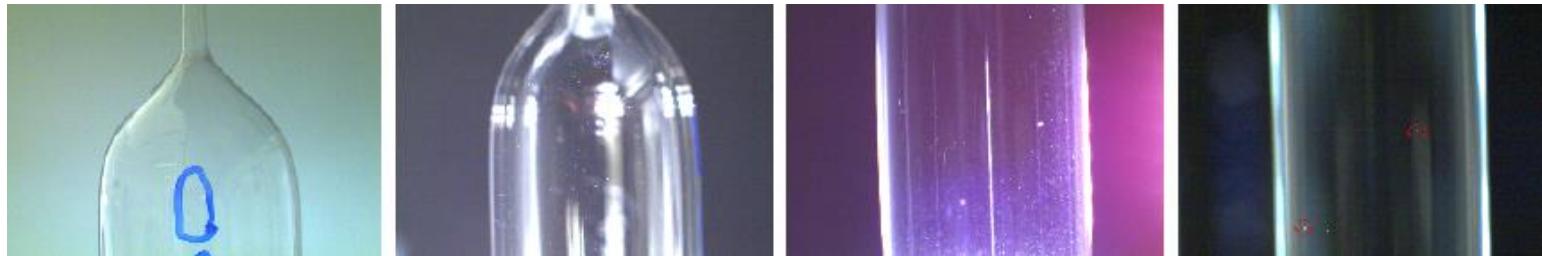


Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.
Lin, Rivenson, Yardimci, Veli, Luo, Jarrahi & Oczan (2018). «All-optical machine learning using diffractive deep neural networks». Science, 26. Jul 2018.

3. Industrial quality control

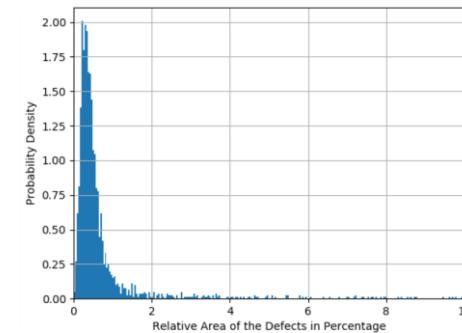
Task

- Reliably **sort out faulty balloon catheters** in image-based production quality control



Challenges

- Non-natural** image source, class **imbalance**, **optical conditions**, **variation** in defect size & shape



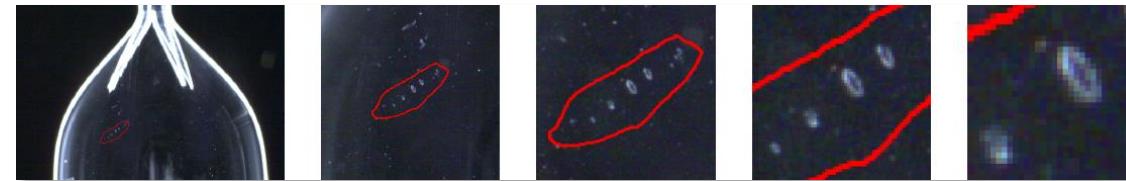
Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

3. Industrial quality control – solutions

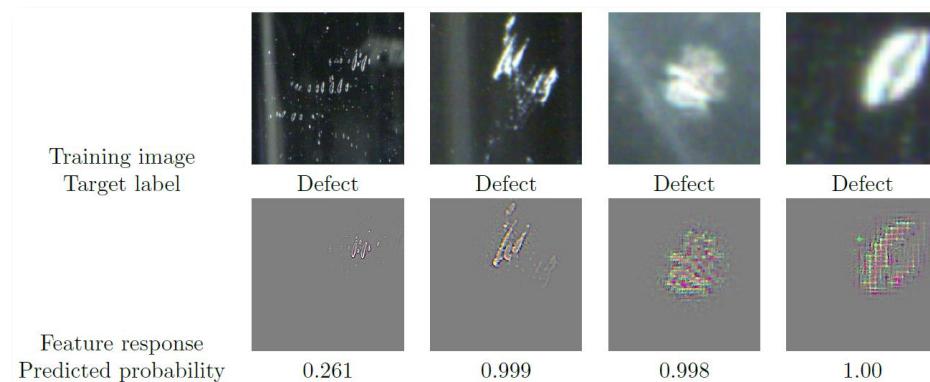
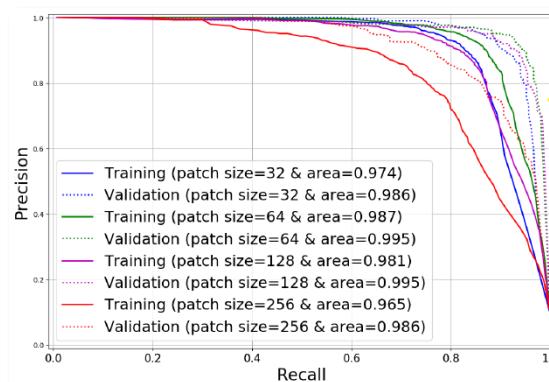
(Work in progress)

Ingredients

- Weighted loss
- Defect cropping
- Secret sauce



Preliminary results

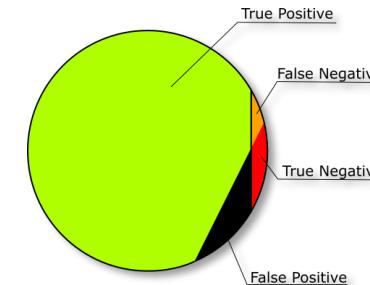


Lessons learned 3/4



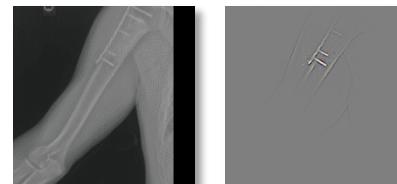
Data

- Acquisition usually **needs much more time** than expected, yet is the basis for all subsequent success
- Class **imbalance & covariate shift** are usual



Understanding

- **What has been learned and how decisions emerge** help both the user and the developer of neural networks to build trust and improve quality



- **Operators and business owners** need a basic understanding of used methods to produce usable ground truth and provide relevant subject matter expertise

Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

Lessons learned 3/4 (contd.)



Simple baselines

- Do a good job in **determining the feasibility** as well as the **potential** of the task at hand when final datasets or novel methods are not yet seen

The image shows two side-by-side browser windows. The left window displays the 'Model Zoo' website, which is a collection of open-source deep learning models. It features a dark header with the title 'Model Zoo' and a subtext 'Discover open source deep learning code and pretrained models.' Below this are two buttons: 'Browse Frameworks' and 'Browse Categories'. A search bar labeled 'Filter models...' is present. Three model cards are shown: 'OpenPose' (8348 stars), 'Mask R-CNN' (6957 stars), and 'Image-to-Image Translation'. The right window displays the 'MURA Dataset: Towards...' website, which is a competition for bone X-ray deep learning. It features a red header with the Stanford ML Group logo and the text 'MU RA Bone X-Ray Deep Learning Competition'. Below this is a section titled 'What is MURA?' with a description of the dataset and its significance. To the right is a 'Leaderboard' section showing a single entry: 'Best Radiologist Performance' with a Kappa value of 0.778.

Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «*Deep Learning in the Wild*». ANNPR'2018.

4. Music scanning



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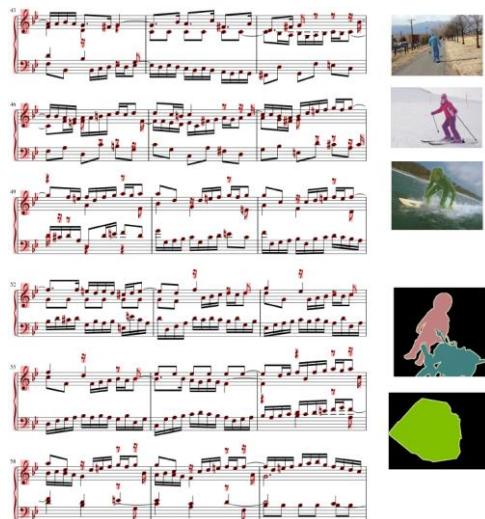


4. Music scanning – challenges & solutions



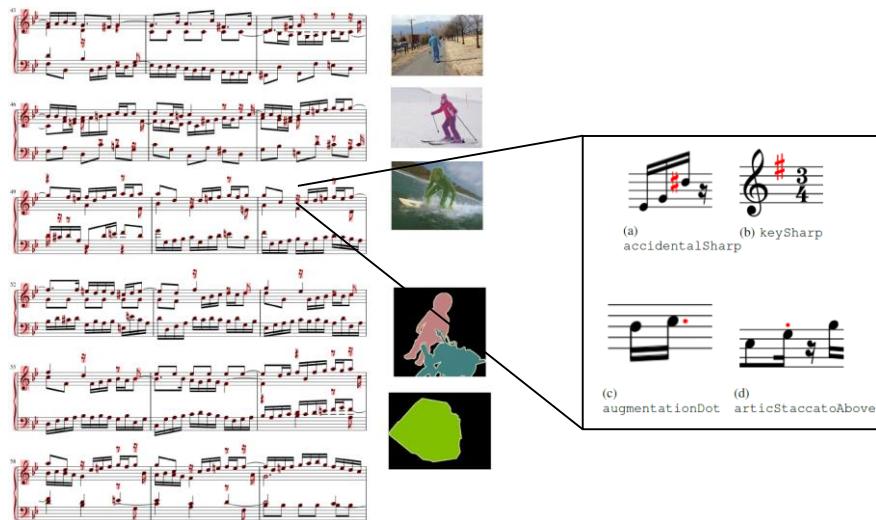
Tuggener, Elezi, Schmidhuber, Pelillo & Stadelmann (2018). «DeepScores – A Dataset for Segmentation, Detection and Classification of Tiny Objects». ICPR'2018.

4. Music scanning – challenges & solutions



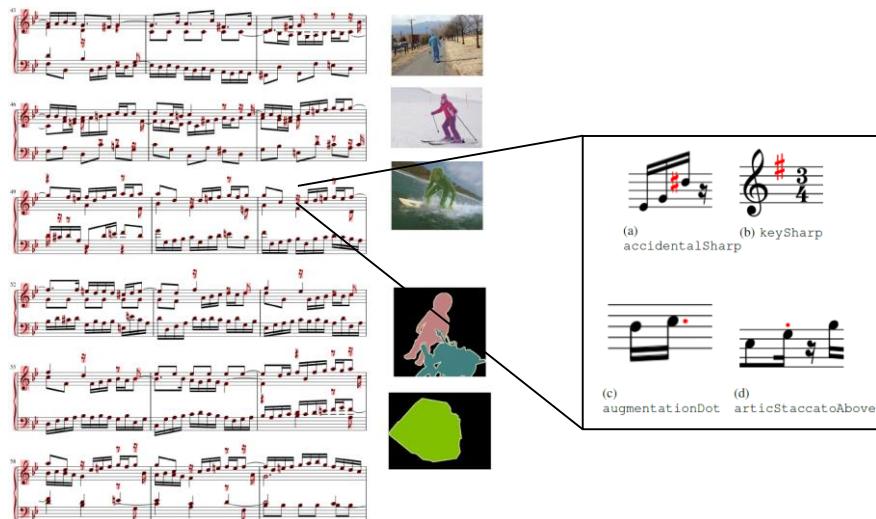
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4. Music scanning – challenges & solutions



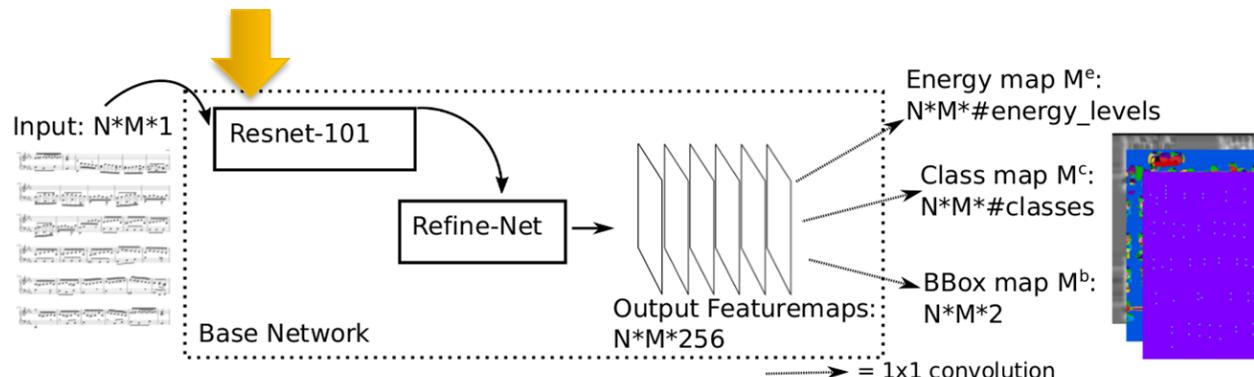
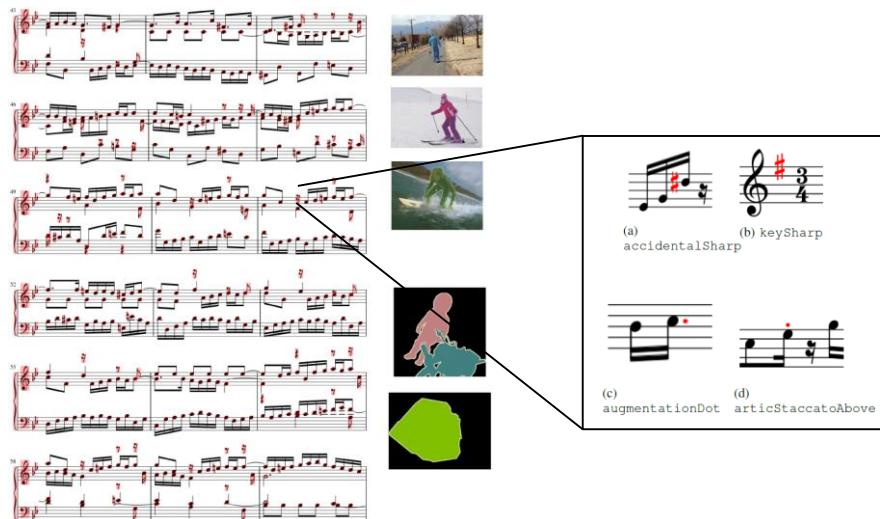
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4. Music scanning – challenges & solutions



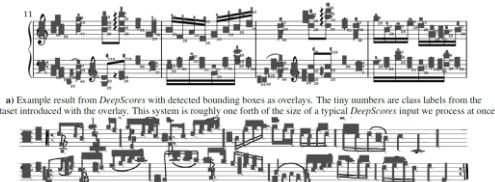
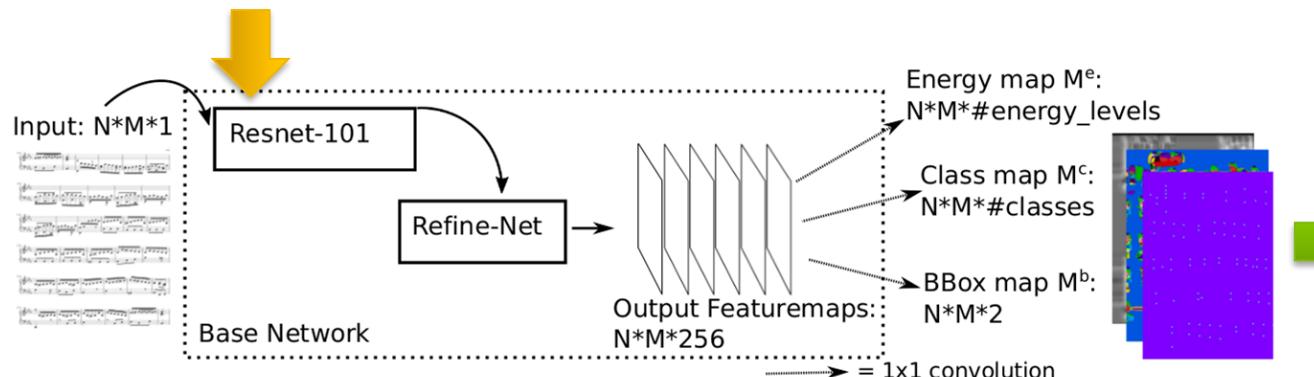
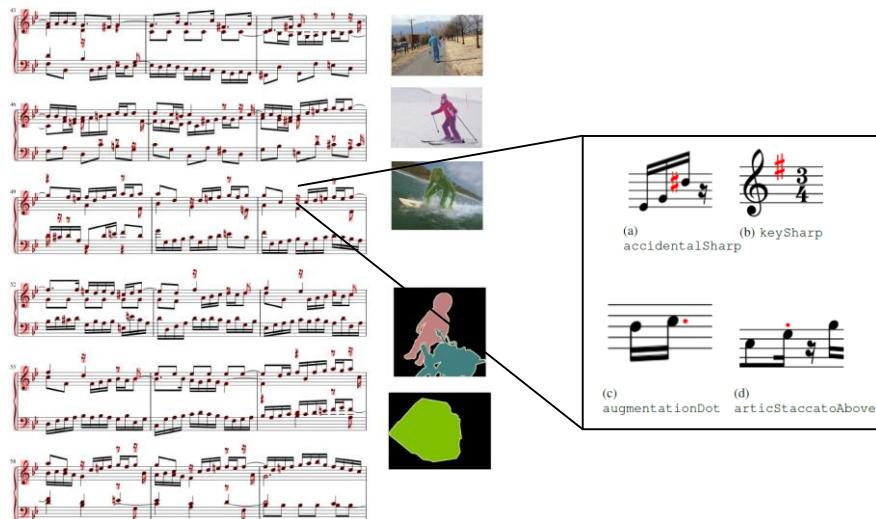
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4. Music scanning – challenges & solutions



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Tuggener, Elezi, Schmidhuber & Stadelmann (2018). «Deep Watershed Detector for Music Object Recognition». ISMIR'2018.

4. Music scanning – challenges & solutions



a) Example result from DeepScores with detected bounding boxes as overlays. The tiny numbers are class labels from the dataset introduced with the overlay. This system is roughly one forth of the size of a typical DeepScores input we process at once.

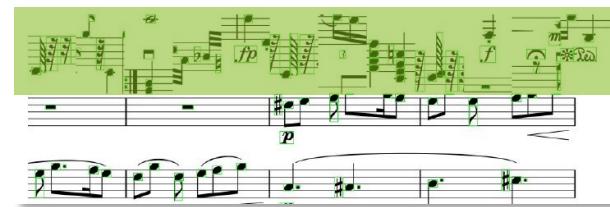
b) Example result from MuSCIMA++ with detected bounding boxes and class labels as overlays. This system is roughly one half of the size of a typical processed MuSCIMA++ input. The images are random picks amongst inputs with many symbols.

Tuggener, Elezi, Schmidhuber, Pelillo & Stadelmann (2018). «DeepScores – A Dataset for Segmentation, Detection and Classification of Tiny Objects». ICPR'2018.
Tuggener, Elezi, Schmidhuber & Stadelmann (2018). «Deep Watershed Detector for Music Object Recognition». ISMIR'2018.

4. Music scanning – industrialization (Work in progress)

Recent results on **class imbalance** and **robustness** challenges

1. Added sophisticated **data augmentation** in every page's margins



2. Put additional effort (and compute) into hyperparameter **tuning** and **longer training**
3. Trained also on scanned (more **real-worldish**) scores



→ **Improved mAP** from 16% (on purely synthetic data) **to 47.5%** on more challenging real-world data set
(previous state of the art: 24.8%)

Elezi, Tuggener, Pelillo & Stadelmann (2018). «DeepScores and Deep Watershed Detection: current state and open issues». WoRMS @ ISMIR'2018.
Pacha, Hajic, Calvo-Zaragoza (2018). «A Baseline for General Music Object Detection with Deep Learning». Appl. Sci. 2018, 8, 1488, MDPI.

Lessons learned 4/4



Loss shaping

- Usually necessary to enable learning of very complex target functions

*“Initially, the training was **unstable** [...] if directly trained on the **combined weighted loss**. Therefore, we now **train** [...] on each of the **three tasks separately**.*

*We further observed that while the network gets trained on the bounding box prediction and classification, the energy level predictions get worse. To avoid this, the network is **fine-tuned only for the energy level loss** [...]. Finally, the network is retrained on the combined task [...] for a few thousand iterations [...].”*

- This includes encoding expert knowledge manually into the model architecture or training setup

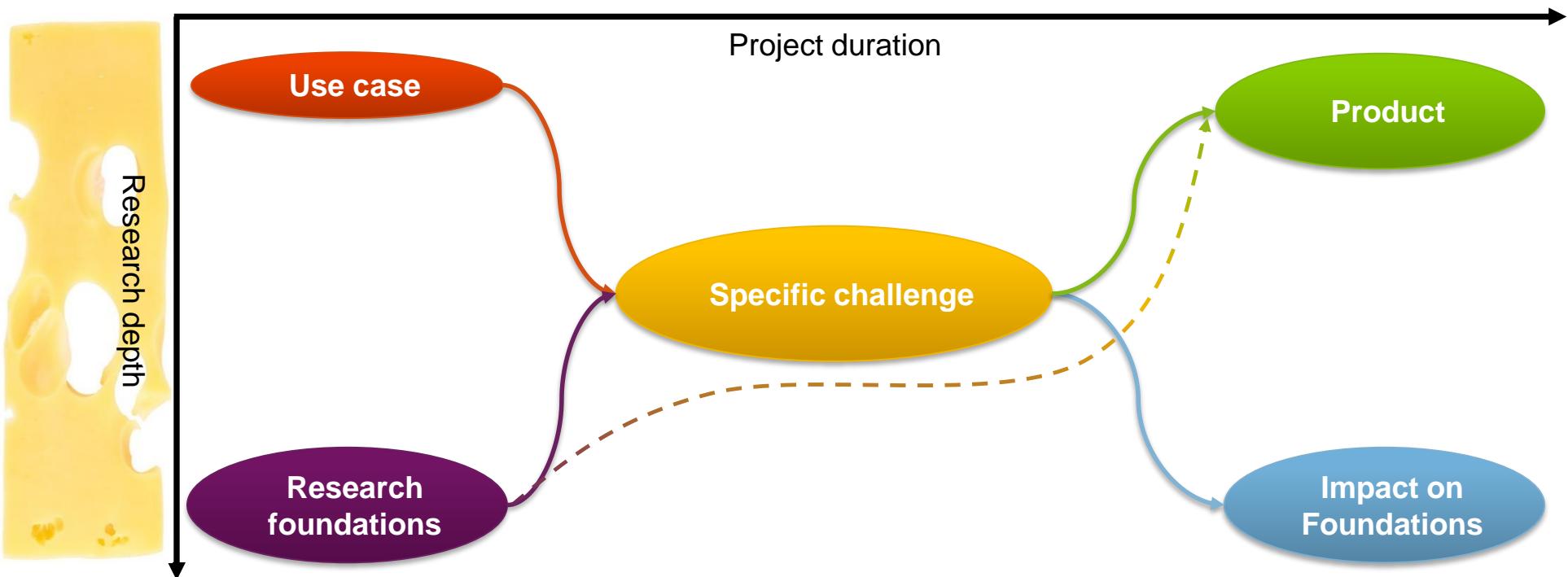
*“The **size of the anomaly** in classifying balloon catheters as good or bad is **quite decisive**. Thus, rescaling the training images is not allowed, and we used a fixed size window around the center of each defect to extract the training images.”*

Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

Hypothesis: basic & applied research converge

Speed of “digital” innovation makes complementary skills necessary at the same time:

- Rigor to come up with completely new methodical approaches
- Creativity to solve completely new scenario, thereby “filling wholes”



Conclusions



- Deep learning **is applied** and deployed in «normal» businesses (non-AI, SME)
- It does not need big-, but some **data (effort usually underestimated)**
- DL/RL **training** for new use cases **can be tricky** (→ needs thorough experimentation)
- The **simultaneity** of research types **A^{pplied}** and **B^{asic}** speaks out loud for **collaboration**



On me:

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- +41 58 934 72 08
- <https://stdm.github.io/>



On the topics:

- AI: <https://sgaico.swissinformatics.org/>
- Data+Service Alliance: www.data-service-alliance.ch
- Collaboration: datalab@zhaw.ch

➔ Happy to answer questions & requests.

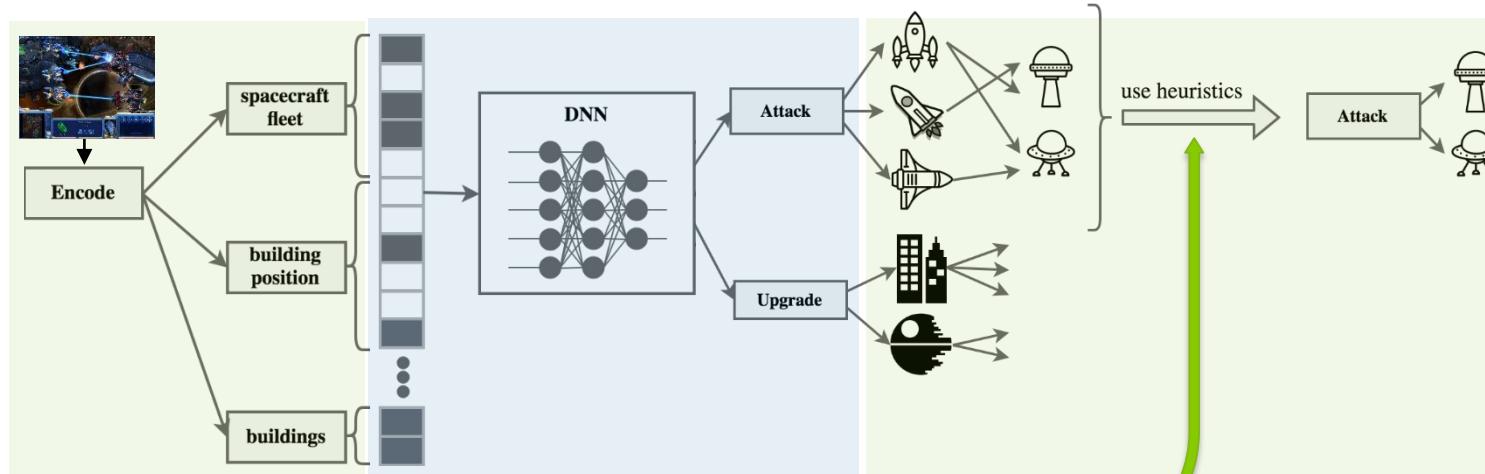


APPENDIX

5. Game playing (work in progress)



5. Game playing – challenges & solutions (work in progress)



Reinforcement learning: deep Q network

Large discrete action space → use heuristic

- makes exploration difficult
- elongates training time



Delayed and sparse reward → do reward shaping

- sequence of actions crucial to get a reward

Distance encoding → use reference points

Transfer Learning → difficult: more complex environment needs other action sequence

Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

6. Automated machine learning

(work in progress)

The project

- Target: inhouse solution of industrial partner to improve turnover in standard analytics projects
- Challenge: optimize hyperparameters smarter than with well initialized random perturbations
- Idea: use reinforcement learning to meta-learn from past analytics projects

Initial experiments

Dataset	Task	Metric	Auto-Sklearn		TPOT		DSM	
			Validation	Test	Validation	Test	Validation	Test
Cadata	Regression	Coefficient Of Determination	0.7913	0.7801	0.8245	0.8017	0.7078	0.7119
Christine	Binary Classification	Balanced Accuracy Score	0.7380	0.7405	0.7435	0.7454	0.7362	0.7146
Digits	Multiclass Classification	Balanced Accuracy Score	0.9560	0.9556	0.9500	0.9458	0.8900	0.8751
Fabert	Multiclass Classification	Accuracy Score	0.7245	0.7193	0.7172	0.7006	0.7112	0.6942
Helena	Multiclass Classification	Balanced Accuracy Score	0.3404	0.3434	0.2654	0.2667	0.2085	0.2103
Jasmine	Binary Classification	Balanced Accuracy Score	0.7987	0.8348	0.8188	0.8281	0.8020	0.8371
Madeline	Binary Classification	Balanced Accuracy Score	0.8917	0.8769	0.8885	0.8620	0.7707	0.7686
Philippine	Binary Classification	Balanced Accuracy Score	0.7787	0.7486	0.7839	0.7646	0.7581	0.7406
Sylvine	Binary Classification	Balanced Accuracy Score	0.9414	0.9454	0.9512	0.9493	0.9414	0.9233
Volkert	Multiclass Classification	Accuracy Score	0.7174	0.7101	0.6429	0.6327	0.5220	0.5153
Average Performance			0.7678	0.7654	0.7586	0.7497	0.7048	0.6991

Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

7. Condition monitoring

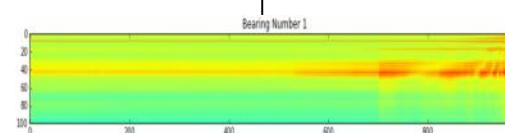
Maintaining machines on predicted failure only

We use machine learning approaches for anomaly detection to learn the normal state of each machine and deviations of it purely from observed sensor signals; the approach combines classic and industry-proven features with e.g. deep learning auto-encoders.

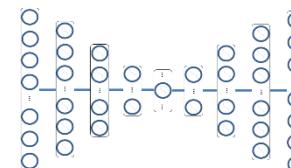
vibration sensors



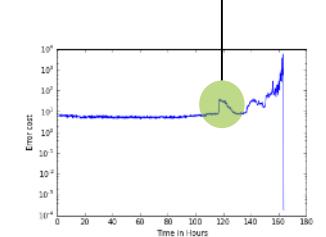
feature extraction



e.g., RNN autoencoder

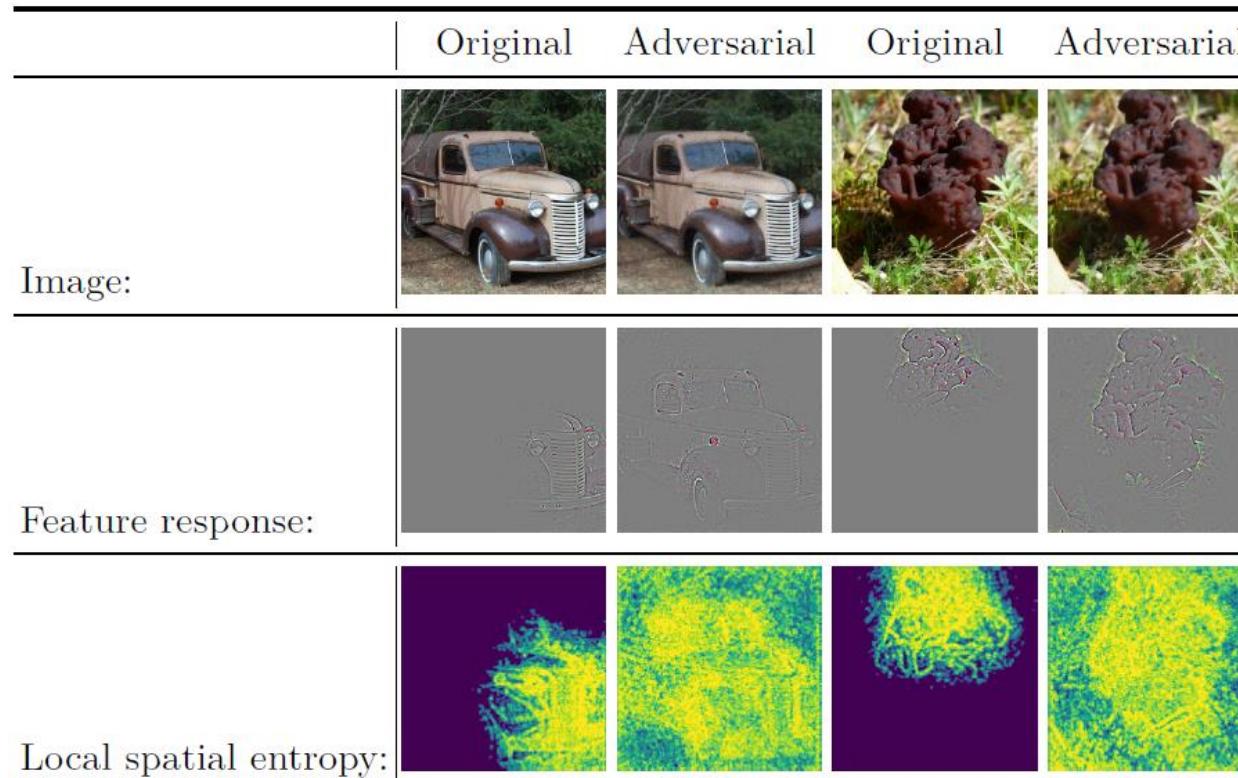


early detection of fault

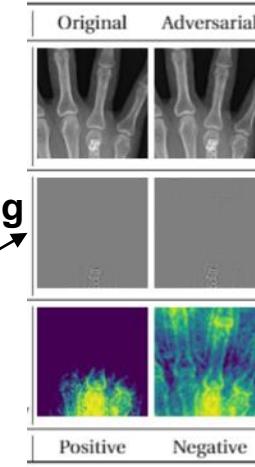


Stadelmann, Tolkachev, Sick, Stampfli & Dürr (2018). «*Beyond ImageNet - Deep Learning in Industrial Practice*». In: Braschler et al., «*Applied Data Science*», Springer.

8. Trace & detect adversarial attacks ...using average local spatial entropy of feature response maps



Amirian, Schwenker & Stadelmann (2018). «*Trace and Detect Adversarial Attacks on CNNs using Feature Response Maps*». ANNPR'2018.



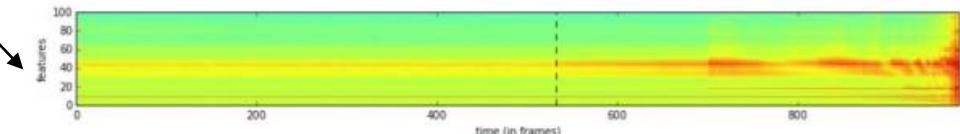
ML @ Information Engineering Group

Institute of Applied Information Technology, ZHAW School of Engineering

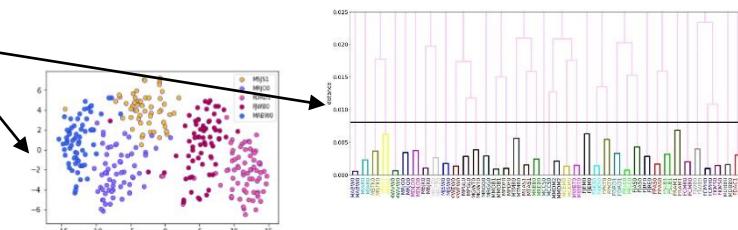


Machine learning-based Pattern Recognition

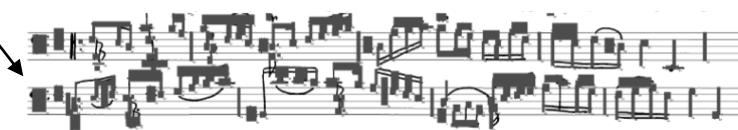
Robust Deep Learning



Voice Recognition



Document Analysis



Learning to Learn & Control

