

Deep Learning in the Wild

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

T. Stadelmann, M. Amirian, I. Arabaci, M. Arnold, G. F. Duivesteijn, I. Elezi, M. Geiger, S. Lörwald, B. B. Meier, K. Rombach & L. Tuggener



Research in the wild and in the lab



Research in the wild and in the lab



Motivated by general progress

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

→ Goal: *fundamental advance in method*

Research in the wild and in the lab



Motivated by application

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

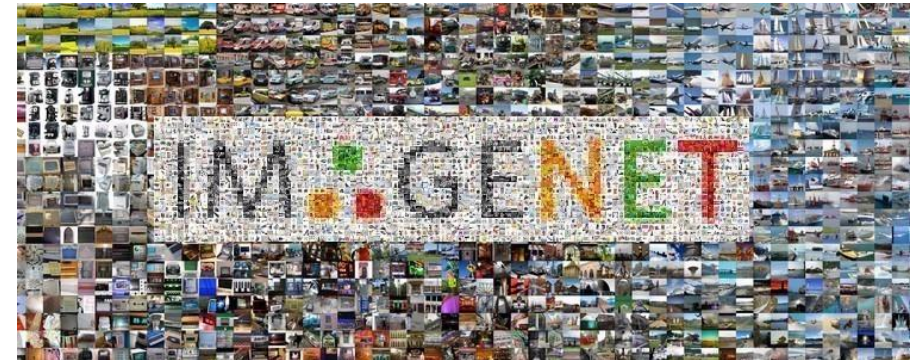
→ Goal: new *product & advance* in method

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Research in the wild and in the lab



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LETTER

Human-level control through deep reinforcement learning

Nandishree Subh¹, Kumar Karthikeyan², David Silver³, Andrew A. Senior⁴, Joel Venema⁵, Marc G. Bellemare⁶, Alex Graves⁷, Martin Riedmiller⁸, Andrew B. Dalrymple⁹, George Ostrovski¹⁰, Greg Deacon¹¹, Charles Beattie¹², Andre Botea¹³, Sumant Venkatesh¹⁴, Hideo King¹⁵, Ilhwan Kim¹⁶, Dhanu Srinivasan¹⁷, Dean Whalley¹⁸, Shariq Legat¹⁹, R. Dennis Haussler²⁰

The theory of reinforcement learning provides a normative account, deeply rooted in psychological and neuroscience, perspectives on animal behaviour, of how agents may optimise their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the world from high-dimensional sensory input and use these to generalise past experience to new situations. Humanlike behaviour and other animals seem to solve this problem through a hierarchical combination of reinforcement learning and humanlike sensory processing systems¹; the former is critical for a wealth of recent theoretical advances^{2–5}, the latter for a wealth of recent theoretical advances^{6–10}. While progress has been made in both, the combination of reinforcement learning and humanlike sensory processing systems to a variety of domains¹¹, their applicability has previously been limited to domains in which useful features can be handcrafted, or to domains with fully observed, low-dimensional state spaces. Here we use recent advances in training deep neural networks^{12–15}, to develop a novel artificial agent, termed a deep Q-network, that can learn successful policies directly from high-dimensional sensory input using only on-line reinforcement learning. We tested this agent on the challenging domain of classic Atari 2600 games¹⁶. We demonstrate that the deep Q-network agent, learning only the pixels and the game score as inputs, was able to surpass the performance of all previous algorithms and achieve a level comparable to that of professional human games testers across a set of 49 games, using the same algorithm, network architecture and hyperparameters. This work bridges the divide between high-dimensional sensory inputs and actions, resulting in the first artificial agent that is capable of learning to excel at a diverse array of challenging tasks.

We used to create a single algorithm that would be able to develop a wide range of competencies on a varied range of challenging tasks – a central goal of general artificial intelligence¹⁷ – that has eluded previous efforts^{18–20}. In addition, we developed a novel agent, termed a deep Q-network (DQN), which is able to combine reinforcement learning with a class of artificial neural networks²¹ known as deep neural networks. Unlike recent advances in deep neural networks^{22–25}, in which several layers of nodes are used to build up progressively abstract representations of the data, here we made it possible for artificial neural networks to learn concepts such as object categories from raw sensory data. We use one particularly successful architecture, the deep convolutional neural network²⁶, which uses hierarchical layers of local convolutional filters to mimic the effects of receptive fields – inspired by Hubel and Wiesel's seminal work on hierarchical processing in early visual cortex²⁷ – to exploit the local spatial correlations present in images. In addition, we introduced a novel technique for stabilising the learning of the network's weights, known as a deep Q-network.

We consider tasks in which the agent interacts with an environment through a sequence of observations, actions and rewards. The goal of the

agent is to select actions in a fashion that maximises cumulative future reward. More formally, we use a deep convolutional neural network to approximate the optimal action-value function

$$Q^*(s, a) = \max_{a'} E \left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} \mid s_t = s, a_t = a, s_0 = s \right]$$

which is the maximum sum of rewards r , discounted by γ at each time step t , achievable by a sequence policy π that chooses an action a_t at each observation s_t and taking an action a_t (see Methods²⁸). Reinforcement learning is known to be difficult to train to converge when a nonlinear function approximator such as a neural network is used to represent the action-value function or Q -function²⁹. This instability has several causes: the correlations present in the sequence of observations, the fact that small updates to Q -values significantly change the policy and therefore change the data distribution, and the correlations between the action values $Q(s)$ and the target values $r + \gamma \max_{a'} Q(s', a')$. We used two key ideas. First, we used a biologically inspired mechanism, known as experience replay³⁰, that randomises over the data, thereby removing correlations in the observation sequence and smoothing over changes in the data distribution (see below for details). Second, we used an iterative update that adjusts the action values $Q(s)$ towards target values that are only periodically updated, thereby reducing correlations with the target.

While other stable methods exist for training neural networks in the reinforcement learning setting, in no neural network Q -learning³¹, these methods involve the repeated training of networks to move on hundreds of iterations. Consequently, these methods, unlike our algorithm, are too inefficient to be used successfully with large neural networks. We parameterise an approximate value function $Q(s, a)$ using the deep convolutional neural network shown in Fig. 1, in which θ are the parameters (that is, weights) of the Q -network, at iteration t . To perform experience replay we store the agent's experiences $s_t, a_t, r_{t+1}, s_{t+1}$ in a first-in-first-out (FIFO) buffer of size N . During learning, we apply Q -learning updates on samples (or minibatches) of experience (s, a, r, s') . $Q(s, a)$ is updated uniformly at random from the pool of stored samples. The Q -learning update at iteration t uses the following loss function

$$L_t(\theta) = \mathbb{E}_{(s, a, r, s')} \left[\left(r + \gamma \max_{a'} Q(s', a') - Q(s, a; \theta_t) \right)^2 \right]$$

in which θ_t is the parameter vector determining the agent's behaviour. θ_t are the parameters of the Q -network at iteration t and θ_{t+1} are the network parameters used to compute the output at iteration $t+1$. The target values $r + \gamma \max_{a'} Q(s', a')$ are only updated with the Q -network parameters θ_t and are held fixed between individual updates (see Methods²⁸).

We consider tasks in which the agent interacts with an environment through a sequence of observations, actions and rewards. The goal of the

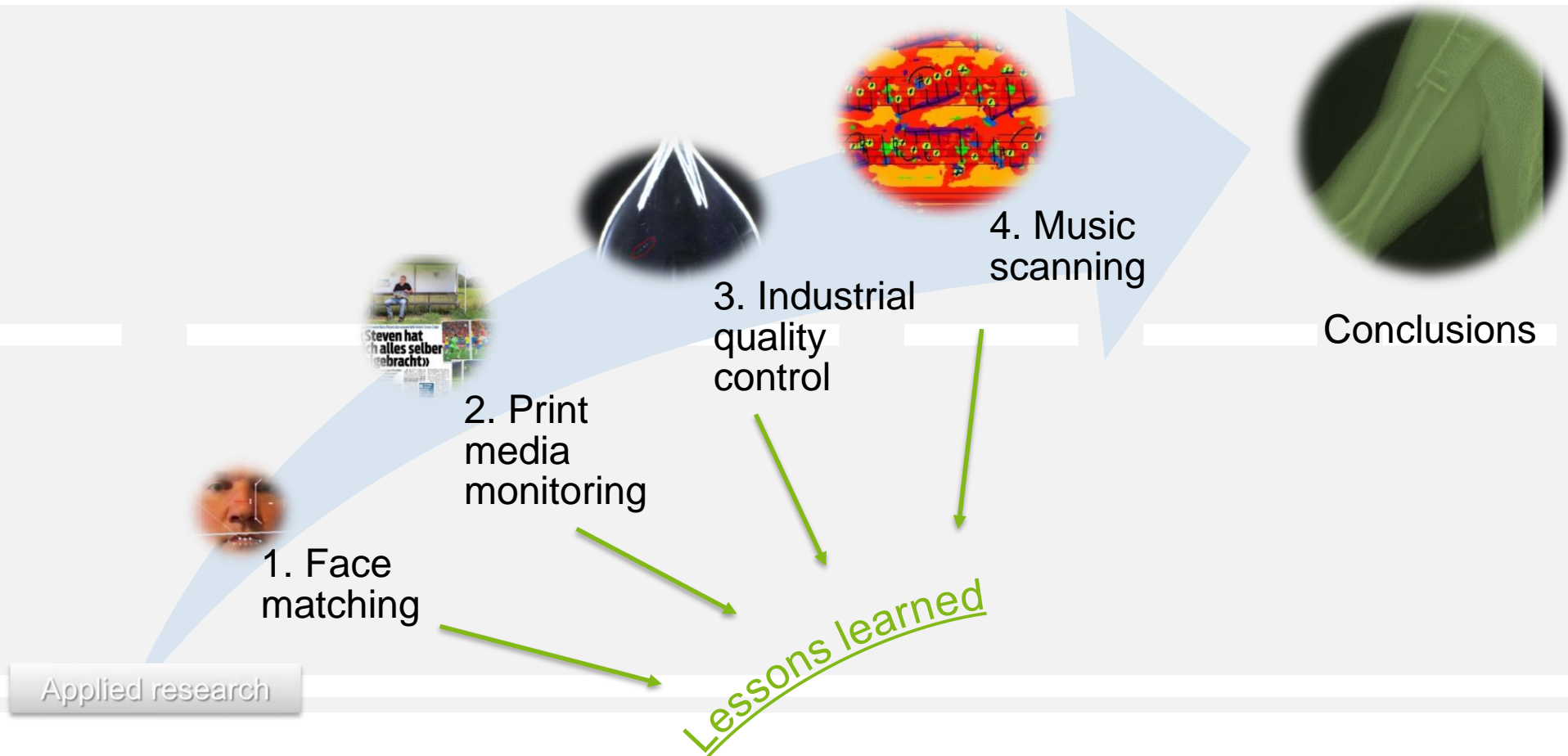
Motivated by general progress

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

→ Goal: *fundamental advance* in method

e.g.

Roadmap



1. Face matching

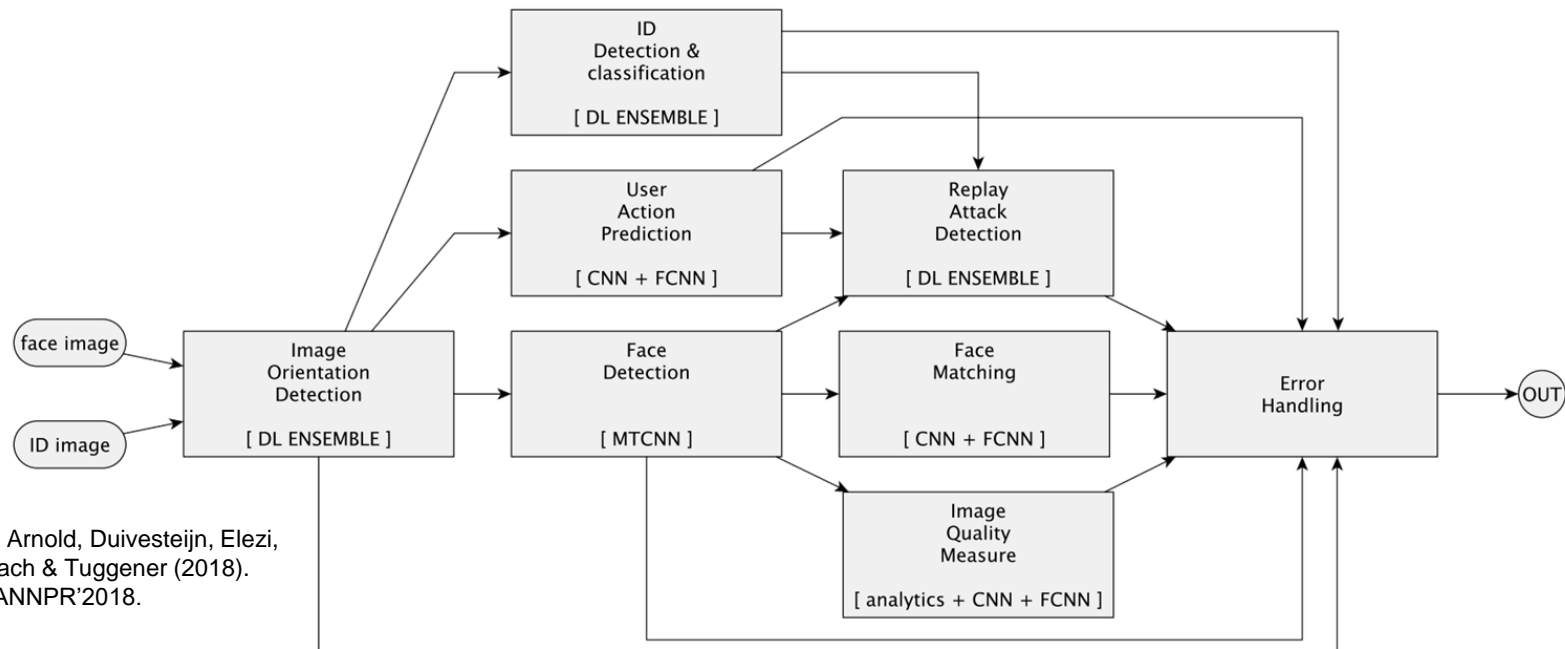


[!] DEEPIIMPACT



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1. Face matching – challenges & solutions




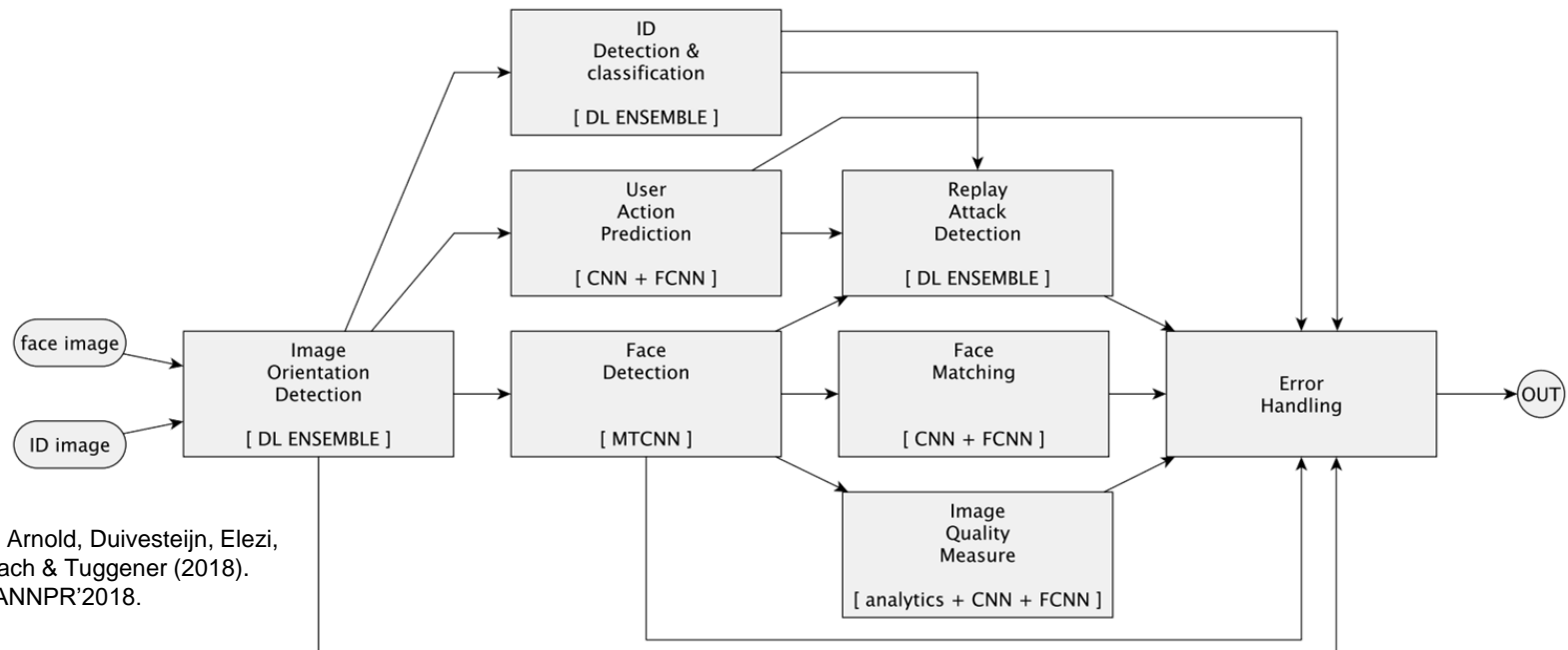
Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

1. Face matching – challenges & solutions



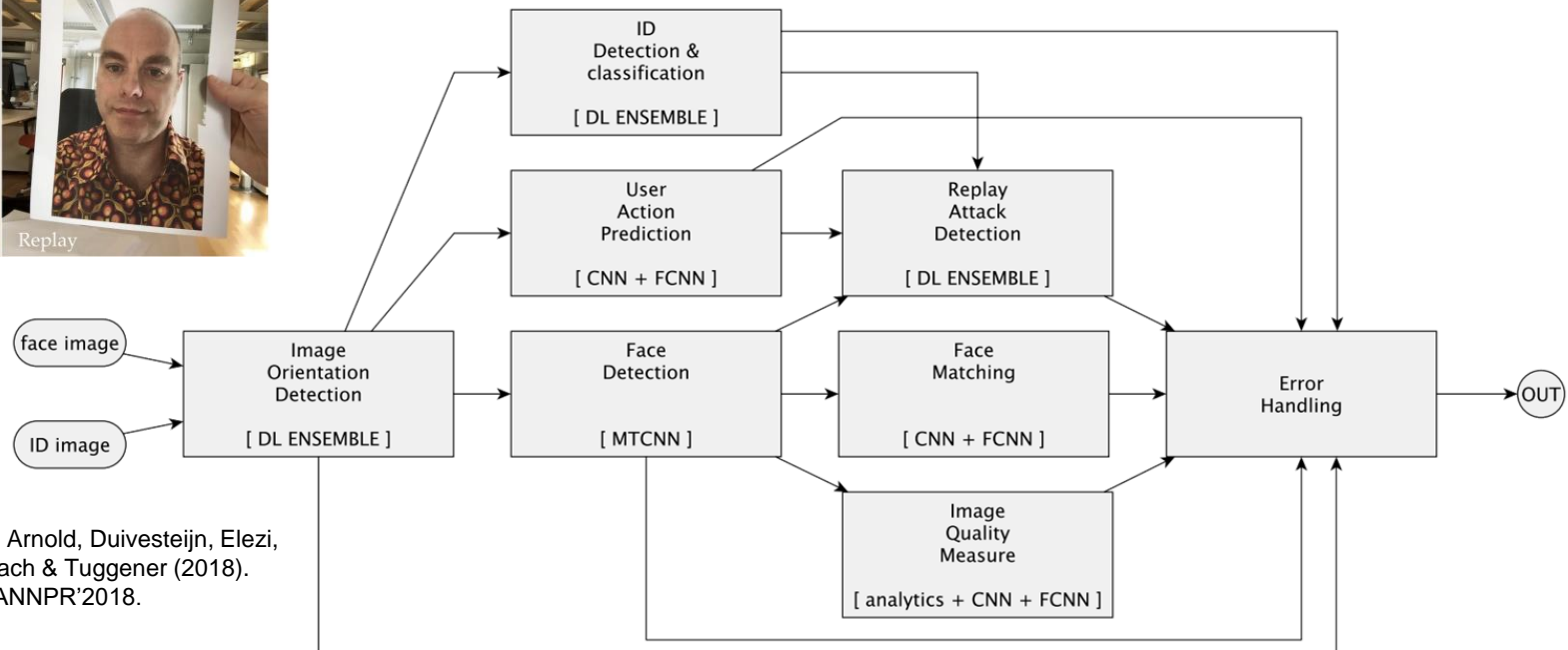
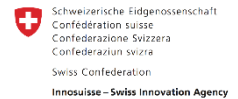
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Stadelmann, Amirian, Arabaci, Arnold, Duivesteijn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

[!] DEEPIMPACT



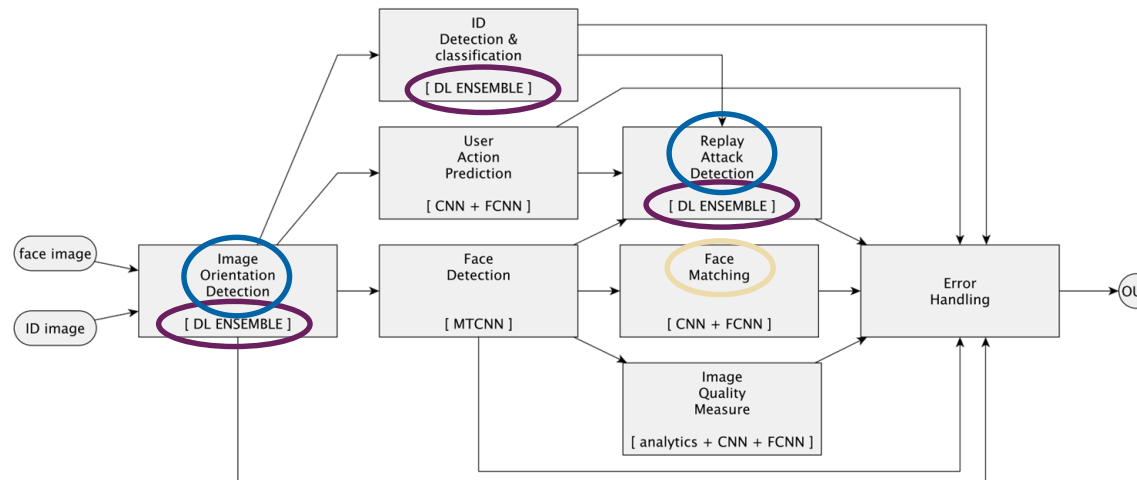
Zürcher Fachhochschule

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.

2. Print media monitoring

Task



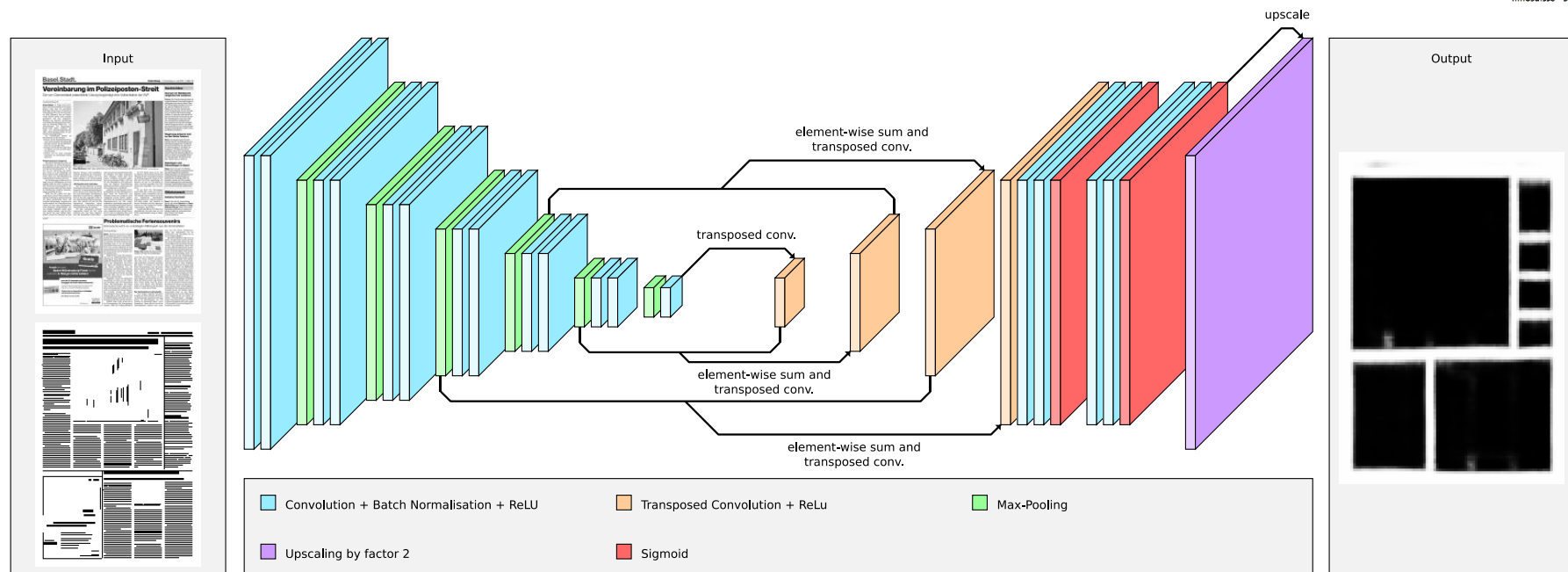
Challenge



Nuisance

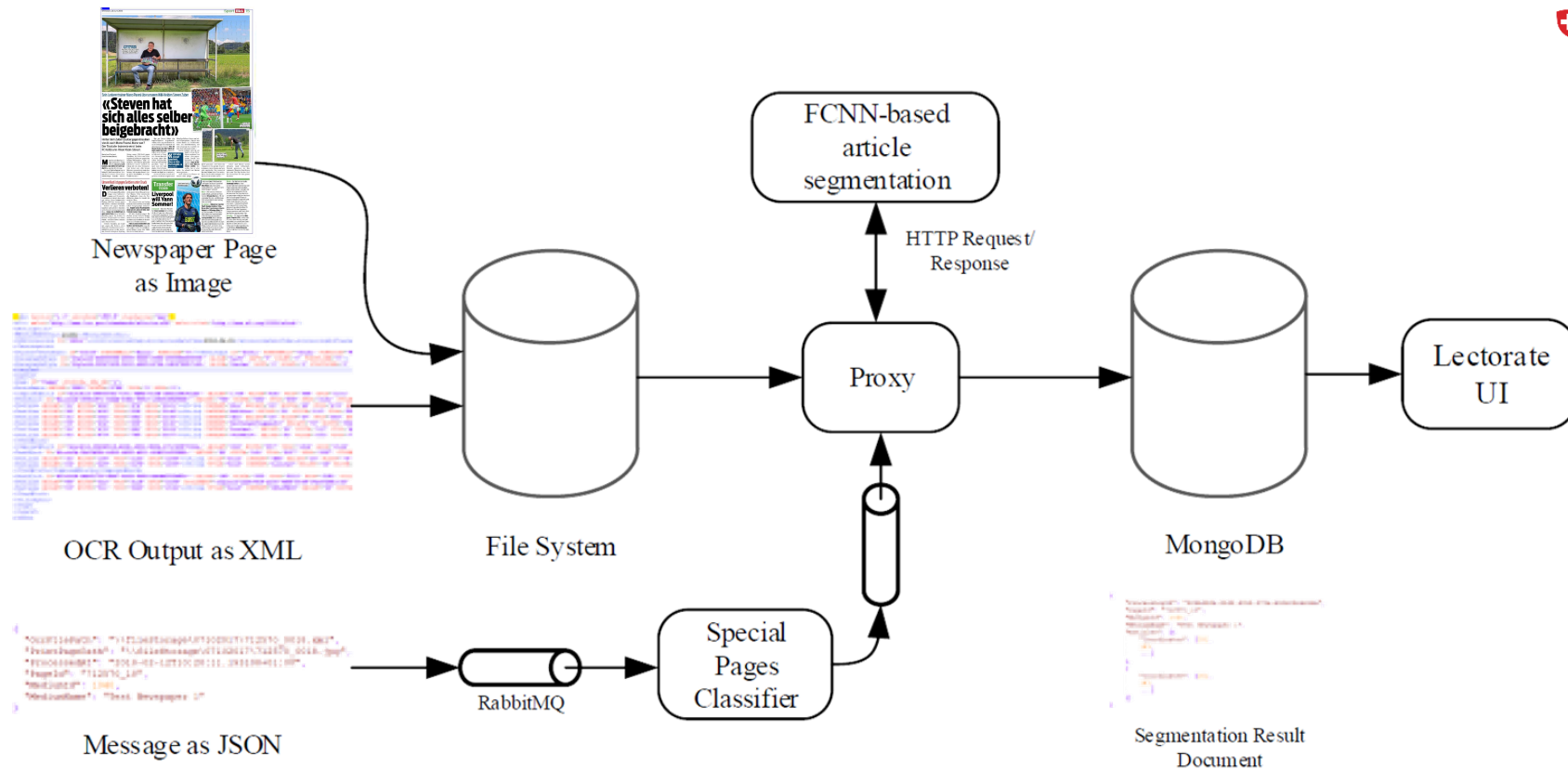


2. Print media monitoring – ML solution



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



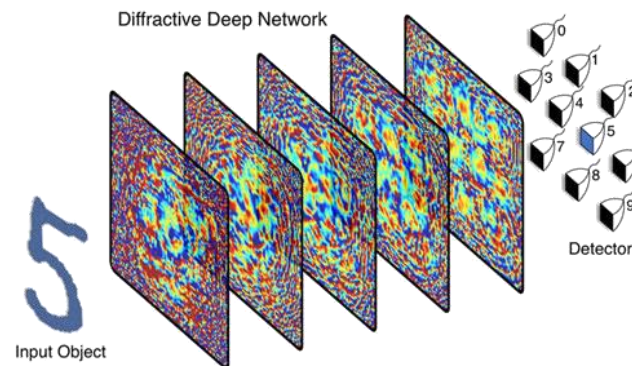
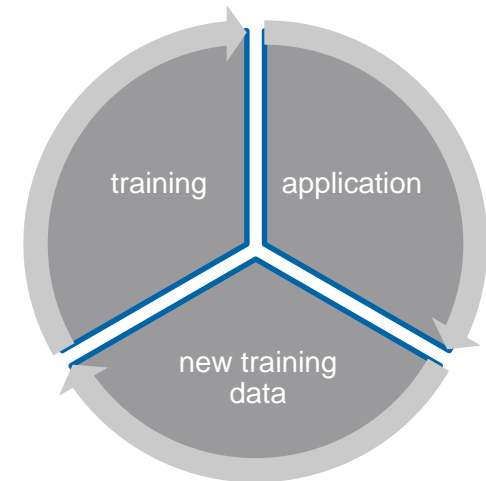
Stadelmann, Amirian, Arabaci, Arnold, Duivesteyn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

Lessons learned 2/4



Deployment

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



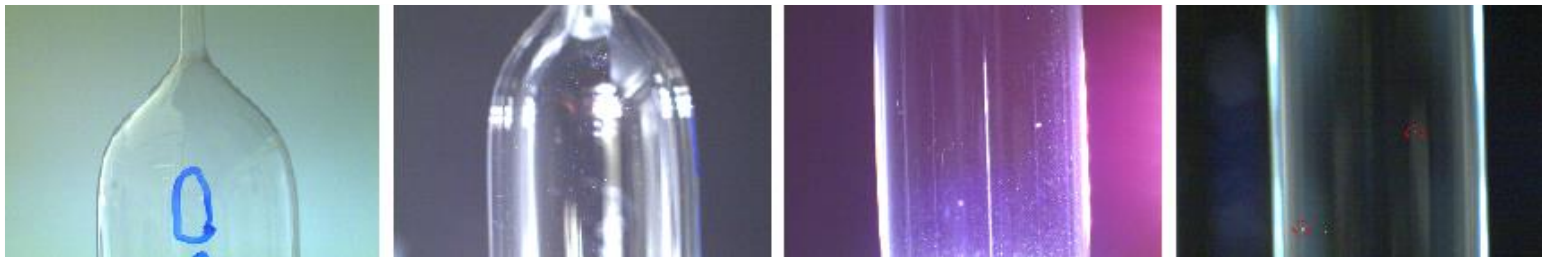
Symbolic image: a CNN in (optical) hardware (Lin et al., 2018).

Lin, Rivenson, Yardimci, Veli, Luo, Jarrahi & Ocuzan (2018). «All-optical machine learning using diffractive deep neural networks». Science, 26. Jul 2018.

3. Industrial quality control

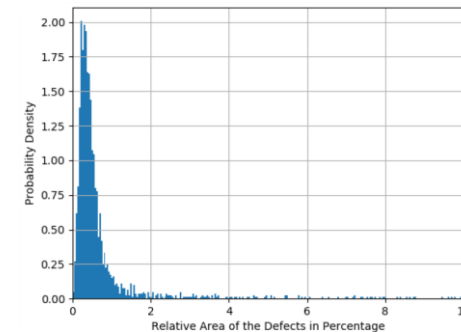
Task

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



Challenges

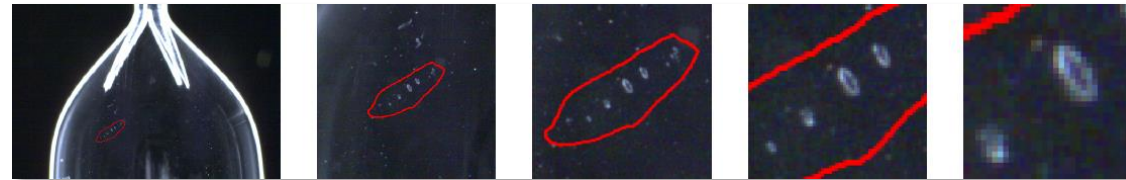
- Non-natural** image source, class **imbalance**, **optical** conditions, **variation** in defect size & shape



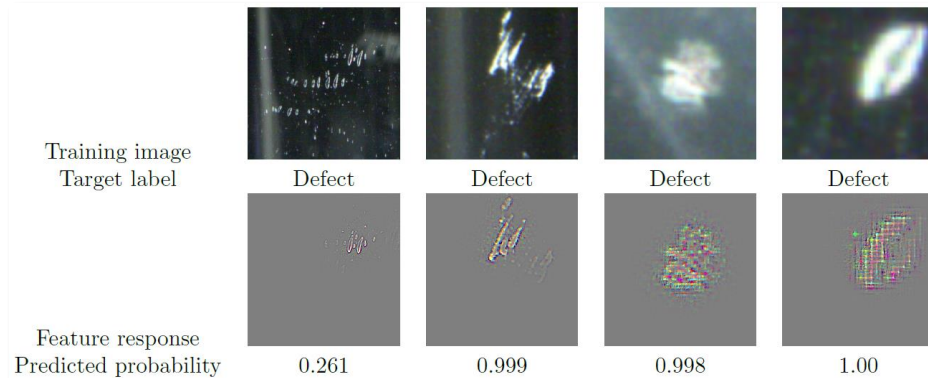
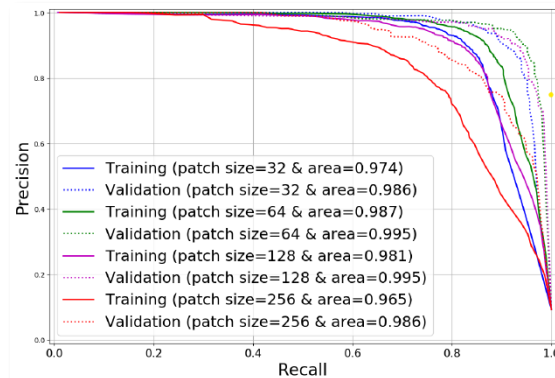
3. Industrial quality control – solutions (Work in progress)

Ingredients

- Weighted loss
- Defect cropping
- Secret sauce



Preliminary results

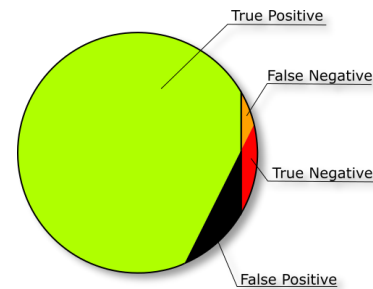


Lessons learned 3/4



Data

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

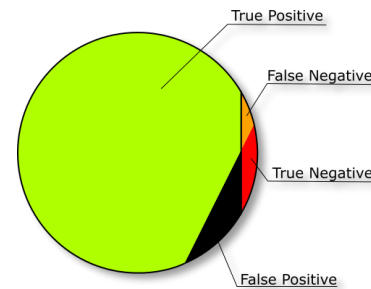


Lessons learned 3/4



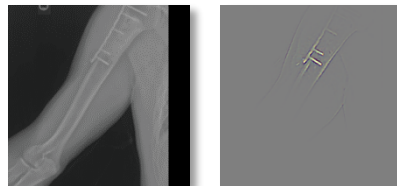
Data

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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



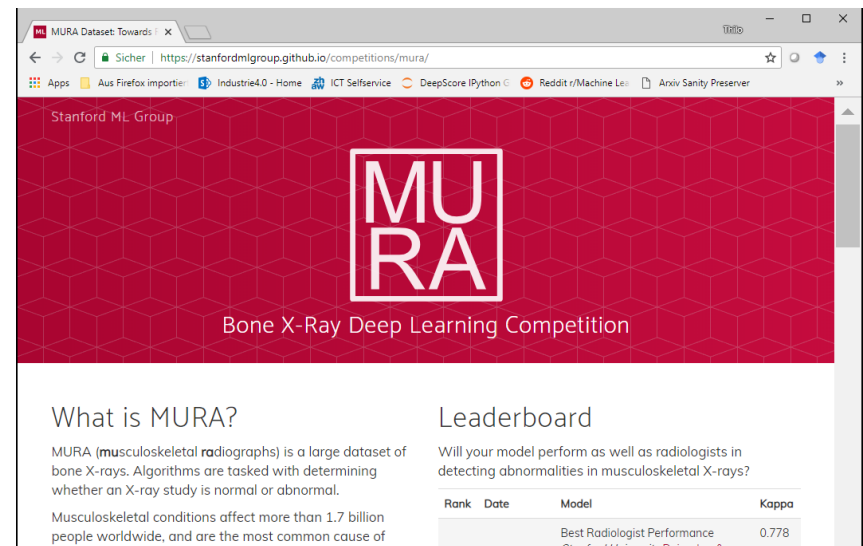
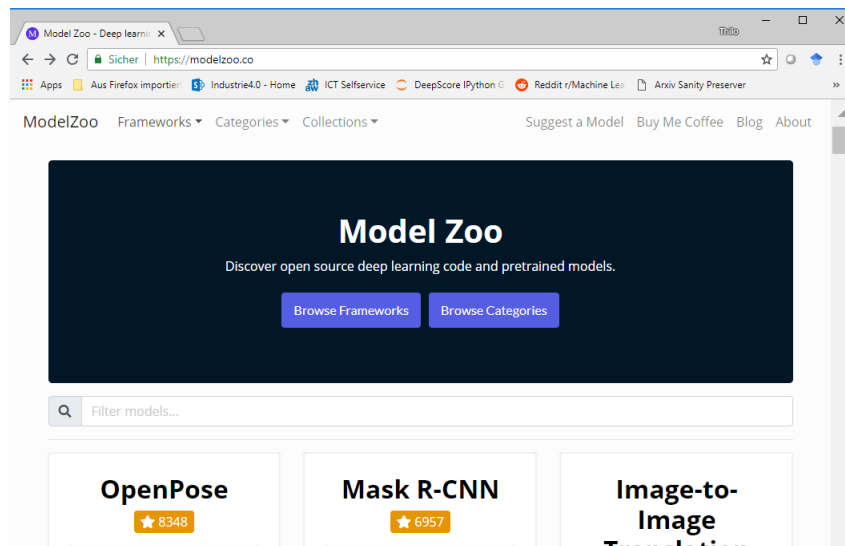
- **Operators and business owners** need a basic understanding of used methods to produce usable ground truth and provide relevant subject matter expertise

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



4. Music scanning

N 132.
Die Forelle.
Gedicht von Ch. Fr. D. Schubert.
Für eine Singstimme mit Begleitung des Pianoforte.
Schubert's Werke. compoſirt von
FRANZ SCHUBERT.
Dritte Fassung.
Nº 231

Melod.

Singstimme.

Pianoforte.



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Die Forelle - Franz Schubert

$\text{♩} = 80$

Voice

Piano

Vo.

ei - nem Büch-lein hel - le, da schoß in fro - her Eil die lau - ni - sche Fo - re - le vor -

4. Music scanning – challenges & solutions



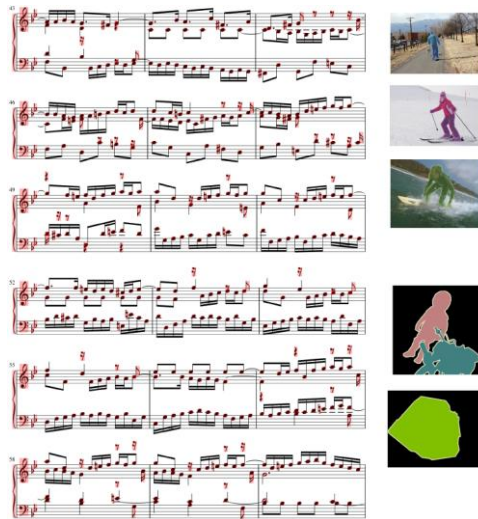
SCOREPAD



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

4. Music scanning – challenges & solutions

(a) accidentalSharp

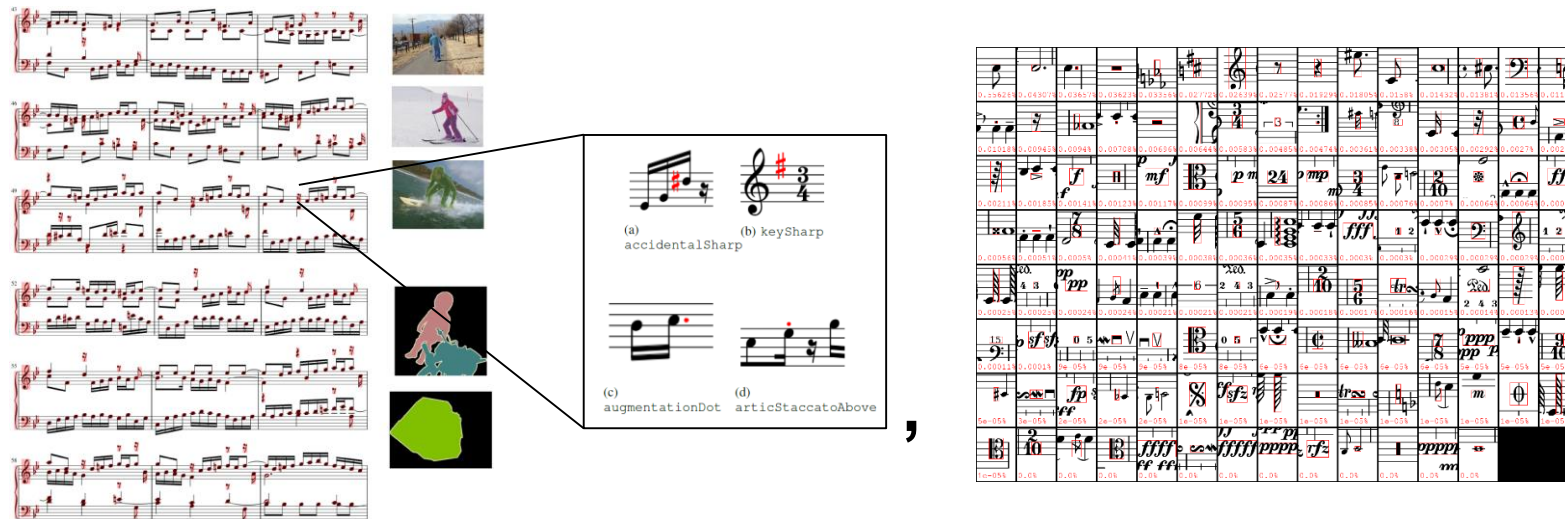
(b) keySharp

(c) augmentationDot

(d) articStaccatoAbove

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

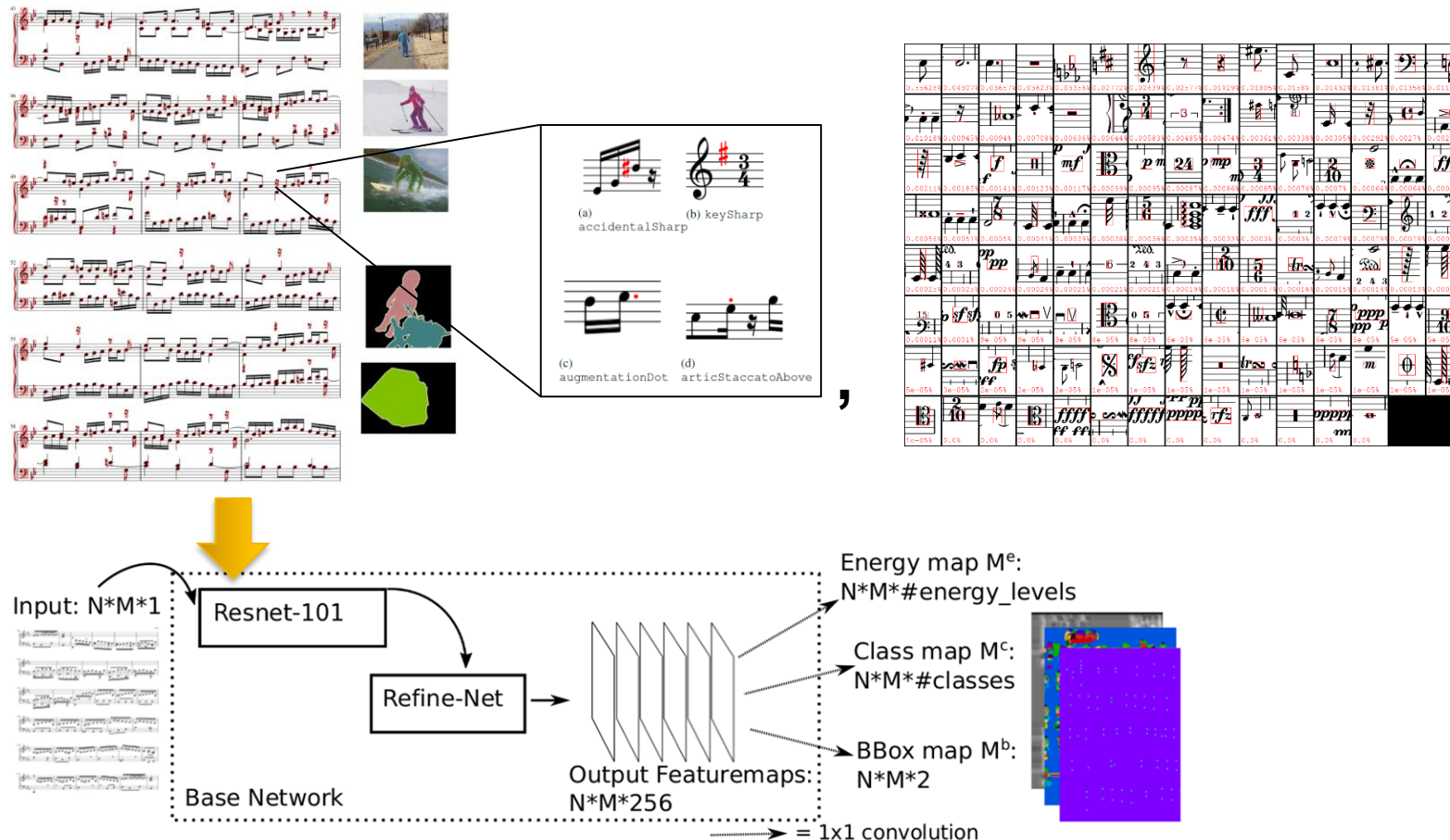
4. Music scanning – challenges & solutions



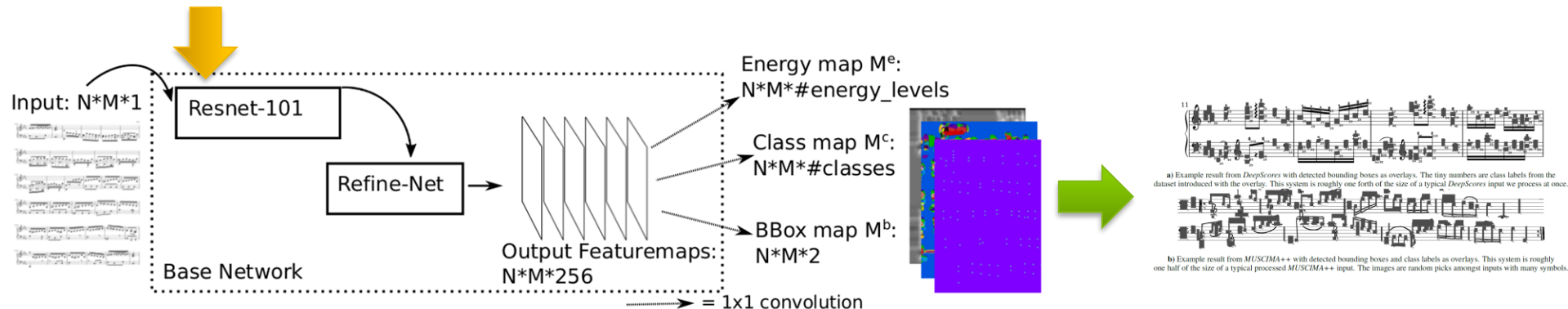
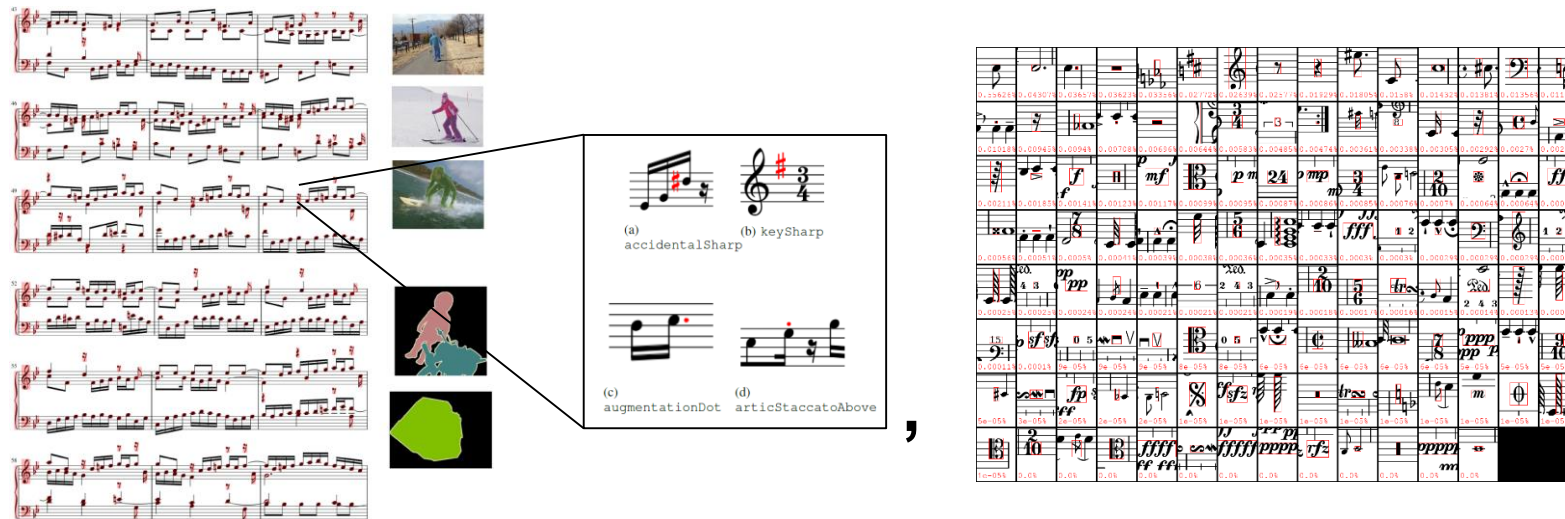
(a) accidentalSharp (b) keySharp

(c) augmentationDot (d) articStaccatoAbove

4. Music scanning – challenges & solutions



4. Music scanning – challenges & solutions



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** our **mAP** from 16% (on purely synthetic data) **to 73%** on more challenging real-world data set (additionally, using Pacha et al.'s evaluation method as a 2nd benchmark: from 24.8% to 47.5%)

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

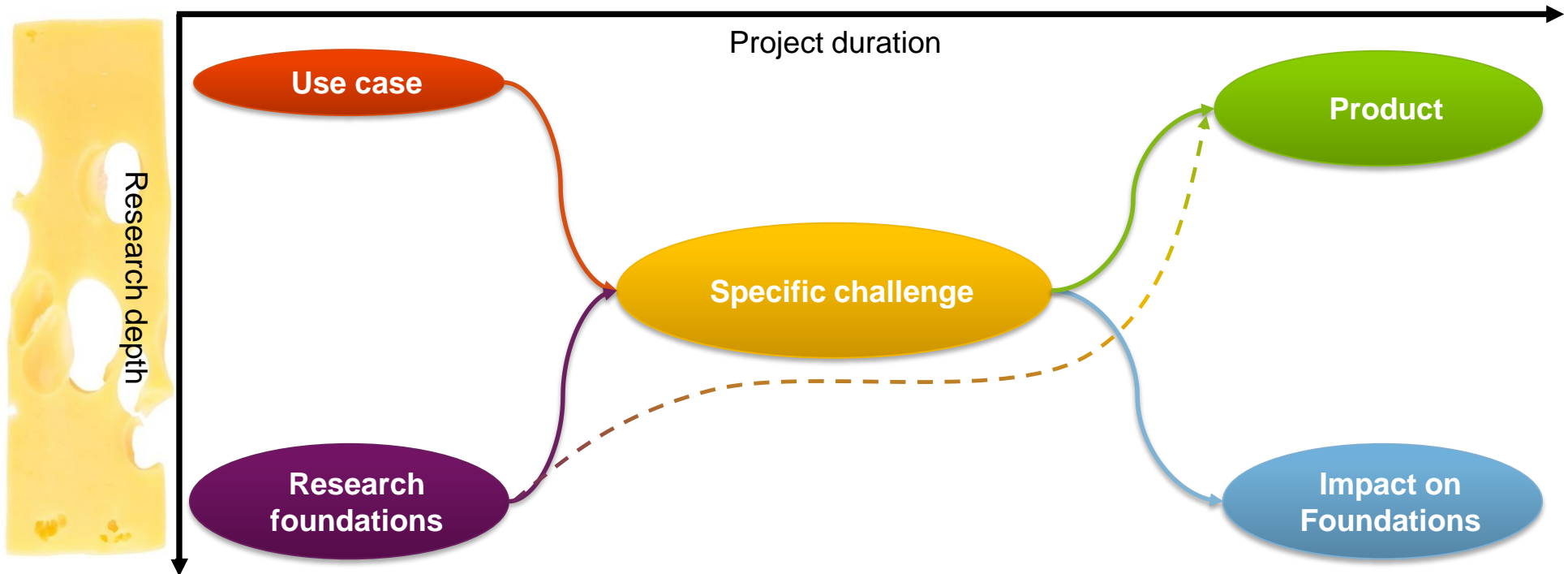
*“The **size of the anomaly** in classifying balloon catheters as good or bad is **quite decisive**. Thus, rescaling the training images is not allowed, and we used a fixed size window around the center of each defect to extract the training images.”*

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

- **Latest research** 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^{pp}lied and B^asic** speaks out loud for **collaboration**



On me:

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- thilo.stadelmann@zhaw.ch
- +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

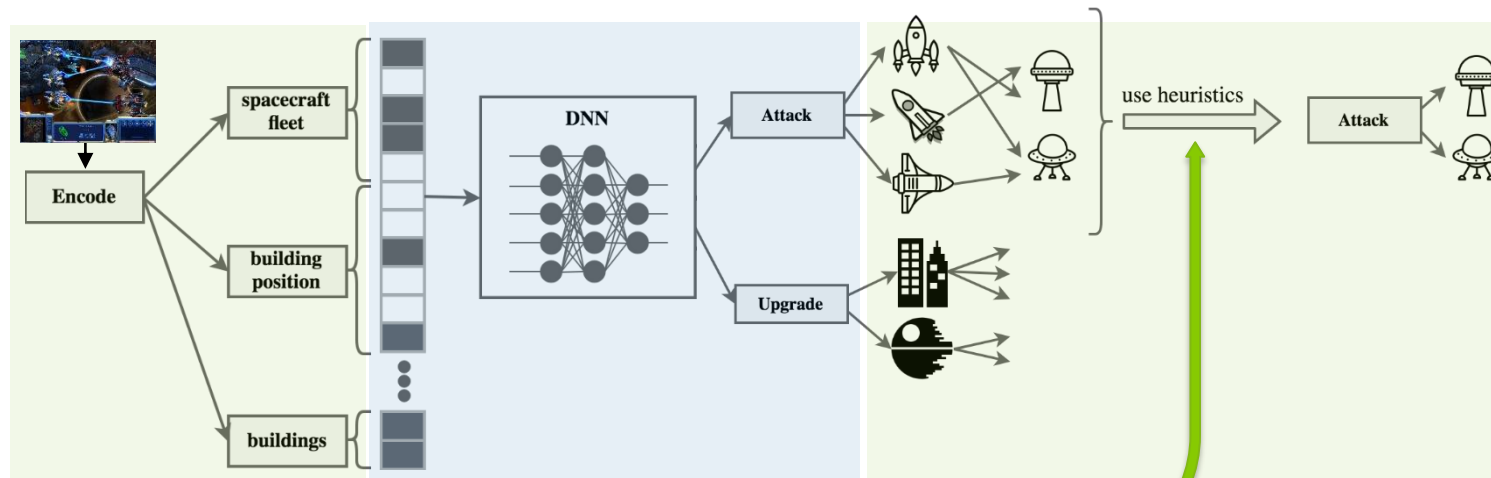
5. Game playing (work in progress)



(symbolic figure)



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, Duivesteyn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

6. Automated machine learning (work in progress)

The project

- Target: in-house 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

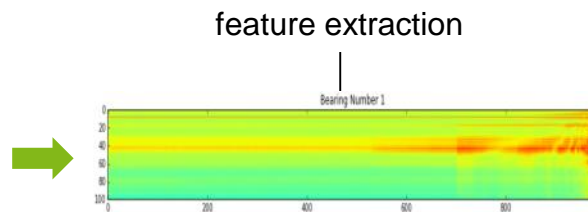
Stadelmann, Amirian, Arabaci, Arnold, Duivesteyn, Elezi, Geiger, Lörwald, Meier, Rombach & Tuggener (2018). «Deep Learning in the Wild». ANNPR'2018.

7. Condition monitoring

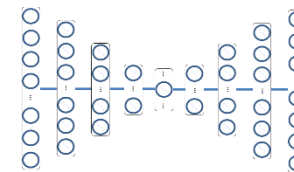
Maintaining machines on predicted failure only

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.

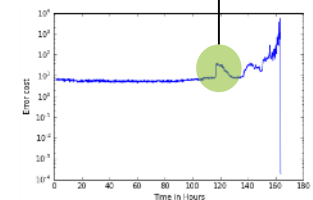
vibration sensors



e.g., RNN autoencoder







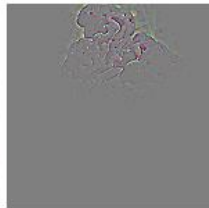
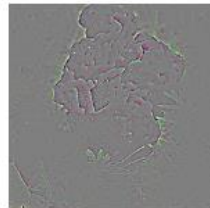
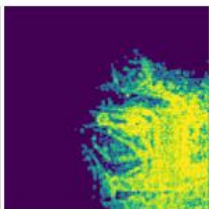
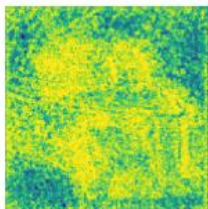
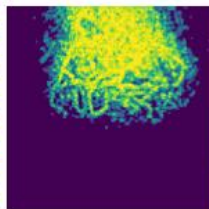
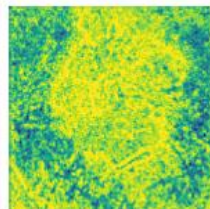


early detection of fault



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

	Original	Adversarial	Original	Adversarial
Image:				
Feature response:				
Local spatial entropy:				

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Machine learning-based Pattern Recognition

Robust Deep
Learning

Voice
Recognition

Document
Analysis

Learning to
Learn & Control

