

Ensemble Methods for Visual Anomaly Detection in Manufacturing Settings

Toller Thesis Titel

Master thesis by Marc Saghir

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1. Review: Super Supervisor
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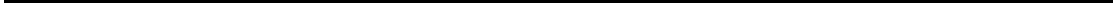
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Mir ist bekannt, dass im Falle eines Plagiats (§ 38 Abs. 2 APB) ein Täuschungsversuch vorliegt, der dazu führt, dass die Arbeit mit 5,0 bewertet und damit ein Prüfungsversuch verbraucht wird. Abschlussarbeiten dürfen nur einmal wiederholt werden.

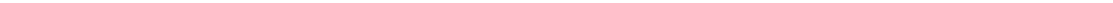
Bei einer Thesis des Fachbereichs Architektur entspricht die eingereichte elektronische Fassung dem vorgestellten Modell und den vorgelegten Plänen.

Darmstadt, 7. Februar 2024

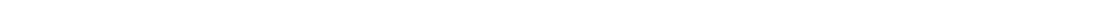
A. Author



Abstract



Abstract



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Abbreviations, Symbols and Operators

List of Abbreviations

Notation	Description
DDPG	Deep Deterministic Policy Gradient
DQN	Deep Q Network
ML	Machine Learning
PPO	Proximal Policy Optimization
RL	Reinforcement Learning
SAC	Soft Actor Critic
TRPO	Trust Region Policy Optimization

List of Symbols

Notation	Description
A	continuous action space
S	continuous state space

$\mathcal{H}(\cdot)$	entropy
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$\pi(a s_t)$	Policy
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1. Introduction

This is a citation: [1]

This is a figure:

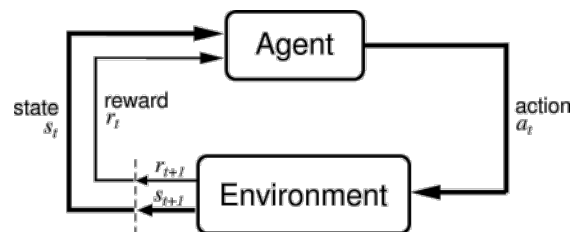


Figure 1.1.: I am a caption

- It is important to note somewhere in the paper that we are dealing with very high variance in our ensemble since we only have 5 models ish

1.1. Begin Intro

In recent years, image anomaly detection has become significantly more important among many scientific communities, especially in industrial applications. This is no surprise, considering the amount of mechanically manufactured parts in factories all over the world. Since in most parts of the world, manufactured items undergo more or less strict regulations and are expected to work in real case scenarios, there is a need for sufficient quality control, that is rising with the amount of produced components. A long time ago, it has come to a point where human based quality checks are not adequate anymore for the production volume, which has led to computer solutions for the problem. Generally speaking, anomaly detection has first been proposed in 1986 for intrusion detection

systems. While the methods and modalities may change, the high level idea stays the same: Detecting data that deviates from a set standard to a degree that is becoming problematic regarding the own requirements (letzer part maybe neu formulieren). Besides many approaches that were used over the years, deep learning approaches for image anomaly detection have become very popular lately. A likely reason for this are impressively high performance scores with state of the art models achieving an area under the receiver operator curve of around 0.96 and sometimes even more. It is difficult to say what the first deep learning approaches to this topic were (data checking), but a notable milestone is definitely Bergmann 2021 (Referenz). Among blabla, they introduced the MVTecAD dataset which is used widely and serves as a dataset to benchmark on for nearly every IAD paper released afterwards. - Übergang benötigt

1.2. Contributions

This work builds upon the researched anomaly detection methods that were established as state of the art over the last years. paper1 and paper2 provide extensive overviews of all SOTA methods, including the ones mentioned here. The main contributions thus are: 1. Creating a pipeline for anomaly detection experiments and inference, utilizing existing IAD approaches. 2. Introducing three new categories for the mvtec(LOCO) dataset for anomaly detection experiments. 3. Researching anomaly detection performance on multi perspective datasets. 4. Experiment on the usage of different ensemble methods for IAD, including utilizing stacking and (die stackig paper von discord zitieren).

The above contributions can be used as basis for industrial usage, as well as a basis for future contributions on ensemble methods in the IAD space. Moreover it gives further insight on the efficiency of SOTA IAD methods on different kinds of data than the previous synthetic settings.

– in my work i contribute the following things: - pipeline to infer new images on different algorithms and compare them -> pipeline is industry focussed for benefits of the guys where i write my thesis

- research on multi perspective detection

- research of ensemble output learning to enhance individual network performance -> simple network over 5-6 outputs

- introduction of very new dataset categories in style of mvtec LOCO dataset

2. Background

This is an algorithm

2.1. Classes of Anomaly detection

When trying to understand the choices of IAD approaches for the pipeline and ensemble, one first has to learn about a few important distinctions of models on this topic. The deep learning approaches that have established themselves as state of the art in image anomaly detection are almost exclusively unsupervised approaches. This partiall stems from the fact that naturally anomalous images occur far less than normal images, hence the word "normal". This is especially true in industrial settings, due to the high performance of production factories nowadays. Therefore if one were to consider using a supervised learning approach to detect anomalies, either a strong class imbalance or an unrepresentative class distribution would occur. While there are some solutions for this, they often are either not good enough for imbalances this high (synonym klänge cool) or far too extensive. Some papers like (supervised papers zitieren) utilize supervised approaches with some success, but still yield a worse performance than the popular unsupervised approaches generally used. Consequently the biggest model distinction is between unsupervised and supervised ones. Here it has to be said that there are technically also other settings of IAD one could talk about at this level of observation, but since we are also directing our focus to RGB images, they will not be talked about. Moreover one has to make some simplifications to allow such sharp categorizations of partially interwoven approaches.

The supervised learning category could also further be split up into sub-categories at a lower level. But seeing as the performances of unsupervised approaches dominantly outweigh the performance and cost of the former, this work will solely focus on the latter kind of approaches. In the unsupervised IAD setting we then normally distinguish between

reconstruction and representation based models. One of the key differences between those two is(hier dringend auch paper zitieren die das untersuchen),

...

If we now consider the classification of algorithms above, aswell as figure x, we can see that there are quite a lot of unique models and approaches to the same end. To ensure that the built pipeline is able to help experiment on images from different points of view, so to say, aswell as ensure that our ensemble approaches cover as various different aspects as possible, it is crucial to select approaches from majorly different branches. Here it may be noted that the performance of the single models is not completely disregarded, as those models may prove themselves not very useful in the ensemble setting or even as a point of view for experimentation. Therefore certain approaches from the survey papers, which yielded performances that were not remotely comparable with the highest performing models, were not considered, even if they might cover a previously unrepresented class of IAD setting. The main choices were: - patchcore + paper - DRAEM + paper - CSFlow + paper

With this choice we still represent reconstruction and representation based settings somewhat comparably, aswell as providing different examples for a variety of subclasses, namely distribution maps, autoencoder, memory banks,

- there are different kinds of approaches to IAD - look at tree picture
- First important distinction is between supervised and unsupervised -> we focus on unsupervised -> list problems with supervised approaches and thus advantages of unsupervised ones
- briefly touch on other IAD settings like few shot, along with references
- among unsupervised approaches, there are two more fundamental distinctions -> reconstruction based vs representation/feature embedding based -> explain difference with lots of references
- for reconstruction based touch on 2-3 base categories like GANs etc and link fundamental papers for GANs etc - for representation based important to explain memory bank, teacher student, and distribution map - explain normalizing flow somehow somewhere in there
- maybe say which algos we chose and what we covered with that

2.2. The Datasets

- mvtec2d Dataset: - cite bergmann papers - very little Datasets - hosrt description of mvtec dataset -> 15 Classes -> grayscale masks -> explain folder structure(maybe with image) -> example images
- mvtec LOCO Dataset - introduced in beyond dents and scratches - before there were only structural anomalous Datasets - but to compare the ability of IAD methods for logical constraints, there needs to be another dataset -> neu formulieren damit es nicht nach copy pasta aussieht
- short description of LOCO dataset

2.3. metrics

- show metrics from survey papers - explain which metrics we used and where the other ones are used - explain also why we used the ones we used, and what disadvantages of other ones where
- touch on paul bergmann paper for sPRO score, say how it is better than pixel auoc and normal pro score, also explain saturation thresholds
- some math formula for calculating the important metrics

2.4. description of patchcore algo

2.5. description of simplenet

2.6. description of AST

2.7. description of DRAEM

2.8. description of another reconstruction based algo



3. Related Work

4. Method

This is an table:

m	$\Re\{\mathfrak{X}(m)\}$	$-\Im\{\mathfrak{X}(m)\}$	$\mathfrak{X}(m)$	$\frac{\mathfrak{X}(m)}{23}$	A_m	$\varphi(m) / ^\circ$	$\varphi_m / ^\circ$
1	16.128	8.872	16.128	1.402	1.373	-146.6	-137.6
2	3.442	-2.509	3.442	0.299	0.343	133.2	152.4
3	1.826	-0.363	1.826	0.159	0.119	168.5	-161.1
4	0.993	-0.429	0.993	0.086	0.08	25.6	90
5	1.29	0.099	1.29	0.112	0.097	-175.6	-114.7
6	0.483	-0.183	0.483	0.042	0.063	22.3	122.5
7	0.766	-0.475	0.766	0.067	0.039	141.6	-122
8	0.624	0.365	0.624	0.054	0.04	-35.7	90
9	0.641	-0.466	0.641	0.056	0.045	133.3	-106.3
10	0.45	0.421	0.45	0.039	0.034	-69.4	110.9
11	0.598	-0.597	0.598	0.052	0.025	92.3	-109.3

Table 4.1.: Table Caption

4.1. Our own Dataset

- repeat motivation why we added additional data in mvtec style - say that we went with loco mvtec flair(maybe give reasons) - say that we came up with a set of structural and logical anomalies for each category - list categories(flat connector, angle and special construct)
- 3 sub sections for the three categories
- flat connector - link the exact one we used(or examples of some) - give structural anomalies
- give logical anomalies - for both briefly touch on how we produced them - show image examples for each
- repeat same for other categories
- also when describing angle: - touch on how there is a special case with multi perspective detection

4.2. pipeline

- explain brief structure of the pipeline - ???

4.3. Ensemble network

- network architecture - specifics

4.4. Different ensemble approaches

- weighted, random forest etc - specifics



5. Experimental Setup



6. Experimental Results

- analysis on how methods worked on own dataset individually -> if poor performance error analysis and also address different subclasses
- analysis of how ensemble model worked and if it improved performance



7. Conclusion and Future work



Bibliography

- [1] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin, “Attention is all you need,” in *Advances in Neural Information Processing Systems* (I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, eds.), vol. 30, Curran Associates, Inc., 2017.



A. Appendix

Appendix here