Ensemeble Methods for Visual Anomaly Detection in Manufacturing Settings

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

Darmstadt, 24. März 2024

M. Saghir

Abstract

Abstract

Contents

Figures and Tables

List of Figures

List of Tables

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
$\pi(a\|s_t)$	Policy

1. Introduction

This is a citation: [1]

This is a figure:

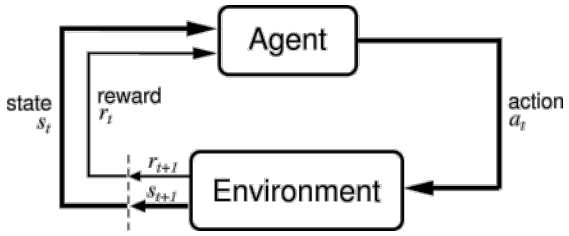

Figure 1.1.: I am a caption

- 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 rather 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(referenz). 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 problematatic 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 operateor curve of around 0.96 and sometimes even more. It is difficult to say what the first deep learning approaches to this topic were(fact checking), but a notable milestone is definetly 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. Table Test Viz

This is a table:

1.3. Contributions

This work builds upon the researched anomaly detection methods that were established as state of the art over the last years. Papers like survey1 and survey2 provide extensive overviews of all SOTA methods, including the ones mentioned in this thesis. The main contributions thus are: 1. Creating a pipeline for anomaly detection experiments and

Metric/Level	Formula	Remarks/Usage
Precision (P) ↑	$P = TP/(TP + FP)$	True Positive (TP), False Positive (FP)
Recall (R) ↑	$R = TP/(TP + FN)$	False Negative (FN), True Positive Rate (TPR)
True Positive Rate (TPR) ↑	$TPR = TP/(TP + TN)$	True Negative (TN)
False Positive Rate (FPR) ↓	$FPR = FP/(FP + TN)$	True Negative (TN)
Area Under the Receiver Operating Characteristic curve (AU-ROC) ↑	$\int_0^1 (TPR)\, d(FPR)$	Classification
Area Under Precision-Recall (AU-PR) ↑	$\int_0^1 P\, d(R)$	Localization, Segmentation
Per-Region Overlap (PRO) ↑	$PRO = \frac{1}{N} \sum_i \sum_k \frac{P_i \cap C_{i,k}}{C_{i,k}}$	Total ground-truth number (N), Predicted abnormal pixels (P), Defect ground-truth regions (C)
Saturated Per-Region Overlap (sPRO) ↑	$sPRO(P) = \frac{1}{m} \sum_{i=1}^{m} \min(\frac{A_i \cap P}{s_i}, 1)$	Total ground-truth number (m), Predicted abnormal pixels (P), Defect ground-truth regions (A), Corresponding saturation thresholds (s)
F1 Score ↑	$F1 = 2(P \cdot R)/(P + R)$	Classification
Intersection over Union (IoU) ↑	$IoU = (H \cap G)/(H \cup G)$	Prediction (H), Ground truth (G)/ Localization, Segmentation

Table 1.1.: Description of metrics

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. Research on incresed robustness in anomaly detection using feature map level ensembles.

The contributions mentioned firstly benefit faster research with a streamlined(synonym) experiment setup. Furthermore they give more insight into the capabilities of existing methods in a industrial setting and thus also provide a more various and practical setting than the prior categories in the mvtec(zitat) dataset. The same methods are also testet on their limitations regarding logical anomalies which is(synonym) a relevant aspect of anomaly detection in current manufacturing quality control. Lastly through the use of a robust ensemble approach for heterogeneous classifers, this opens up possibilities for expanding the field of application of SOTA IAD methods to other domains with robust performance and may also produce more usable results in real world IAD settings.

The above contributions can be used as basis for industrial usage, aswell 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 occurr 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 goo enough for imbalances this high(synonym klänge cool) or far to 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 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 dominantely 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, teacher-student models, diffusion models and ...

- 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

The datasets used in image anomaly detection are scarce, especially when it comes to anomaly detection in a manufacturing setting. There are a few that specialize on certain textures(references) and some that can be used for wide ranging categories. What currently stands out as a gold standard among IAD datasets is the MVTecAD(referenz) dataset. It was designed by Bergman et al.(referenz) as a highly representative and standardized set of anomalous images along with training images. It has 15 classes from (some examples) to (...). It provides image labels aswell as segmentation ground truths, making it versatile and applicable for multiple algorithms. The masks come as black and white grayscale images, while the iamge labels are given through its folder structure. Its paradigmatic structure tree can be seen in figure xy.(hier ein satz der die ordner struktur beschreibt) Example images of the dataset are to be seen in figure z. They typically are of a rectangular shape and their resolutions range from blabla to blabla. More specifications can be found in (mvtec reference) and the whole dataset is publicly available at (dataset link).
The MVTecAD(referenz) dataset is regarded as the go to dataset(wissenschaftlich formulieren) among IAD papers, and has since its introduction been used in nearly every

paper as a dataaset to benchmark ones approaches on. This is also likely to remain the trend, since many important algorithms in the recent years have primarily been benmarked on it, forcing new approaches to also be benchmarked on this dataset to be comparable to the current SOTA approaches. Due to its importance MVTecAD is one of only two datasets relevant to this work, and serves as a comparison to investigate SOTA algoithm performances of the second dataset, which will be our main focus.
Later in (loco year) Bergman et al(referenz) has introduced another IAD dataset that is loosely related to their original MVTecAD dataset, namely the MVTecAD LOCO dataset(reference). This dataset works with the same ground ideas as their original MVTecAD set, but extends the conceptual contents of the dataset by logical anomalies(neu formulieren das klingt scheiße). It consists of five class:(class names). The difference to the other dataset is that the anomalous categories for each class are only seperated into good images, images with structural anomalies and images with logical anomalies. Structural anomalies being visible damages to the objects, similar to the MVTecAD dataset. Logical anomalies denote violations against arbitrary restrictions imposed by Bergmann et al.(referenz). To illustrate this by an example: The class of pushpins represents a birds view of a compartmentised box of pushpins(see figure a). A rule added was, that each compartment is only to contain one pushpin. This means that if one region were to miss their contents, or contain two pushpins, it would constitute a logical anomaly. If on the other hand a pushpin would have a crooked or broken tip, it would be a structural anomaly. The addition of logical constraints opened an interesting area of research, since the high performance of current SOTA algorithms were only measured on structural anomalies so far. Yet it would be insightful to see if those models could also detect logical anomalies, since those also ocurr in real life settings, such as manufacturing settings. (Noch ansprechen dass LOCO eine neue metric -> sPRO ermöglicht und die saturation configs ansprechen) Bergmann et al.(referenz) also released a new IAD model together with the new dataset. The model uses autoencoders(bissi besser beschreiben hier). Unfortunately the code has not been made public. Aside from approaches tailored specifically towards the detection of logical anomalies, it would be interesting to see how SOTA methods of structural anomaly detection perform on the LOCO dataset. The performance of previous methods on the LOCO dataset is already partially evaluated in some papers like(referenzen von benchmark papers),

but will comprehensively be investigated later in this work. Moreover the novel dataset categories introduced later are composed of structural aswell as logical anomalies and formatted in the MVTecAD LOCO dataset style. Aside from the conceptual differences in the two datasets, there are slight changes to the structure tree aswell. The anomaly classes are only changed by name, since it is irrellevant for the models whether the anomaly name is ""

anmerkungen für text oben: - beschreiben was mvtec neu bringt: zb dass es näher an real world ist - saturation thesholds ansprechen

2.3. metrics

- show metrics from survey papers - some metrics are well known from other ML applications - metrics that are important for our work/in most recent published papers are: -> auroc: image/instance and pixel level -> Area under PRO -> explain formula

-> sPRO for LOCO and also Area under sPRO –> Extra section where i explain sPRO on basis of dents and scratches paper –> very detailed with saturation threshold and also include figure of comparison for PRO

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

4.1. Our own Dataset

As previously mentioned in the introduction, this work will also discuss the introduction of three new dataset classes as an addition to the current ones present in the MVTecAD LOCO dataset. This was to extent the range of objects represented in datasets (referenz auf mvted und loco) and further investigate model performance on industrial manufacturing parts, as this is the mein setting for this work. Shaping the dataset in form of the MVTecAD LOCO dataset has multiple advantages. Firstly we get to make statements about the ability of SOTA algorithms detectig logical anomalies on industrial parts. Moreover we can easily infer our new datasets with all relevant IAD approaches, since they are nearly all published with MVTecAD benchmarkings, meaning they are all released with code to infer on the dataset. As discussed in section (dataset section) the only technical difference between the MVTecAD and LOCO dataset is the storage of the masks, which can be accounted for with a few minor changes in the dataset code representation. Since this work also compares AD performances of approaches between both datasets, the functionality is already implemented in the linked repository as a result. This makes for uncomplicated inference on the new dataset. Lastly these dataset classes may serve as a base for future benchmarking and research of different new IAD approaches. Therefore it is sensible to release the new dataset in the shape of if not the most referenced image anomaly detection dataset(beweis oder umformulieren). The three classes are each representing a metal part, namely a flat connector, an angle and ... . For the first to classes, each part that was

acquired for the images is available in a usual hardware store. The third class was a self crafted composite part made of screws and metal sheets, which were also available to buy at similar stores as the other parts. All of the classes meet certain criteria in regards to their material nature, aswell as the possibilities of structural and logical anomalies both occuring with the same part. A solid block of steel for example would make a difficult part to represent logical anomalies. Regarding the recording of images for the dataset, we used (kamera specs) from a birds eye view (nachschauen ob das so heißt) with black cloth (maybe cloth ersetzen und spezifizieren dass es dichtes schwarzes material war) as background. The anomalies were handcrafted in the facilities of the university(suchen wie der werkzeugraum heißt und satz neu formulieren). The labels were done in the same style as the labels of the MVTecAD LOCO classes, meaning black and white segmentation images, with slightly differing pixel values to match according saturation scores.

!Subsection mit flat connector!: For the flat connector we used (maße angeben) regulatory flat connectors (wenn ich lustig bin noch DIN angeben) which are widely available (maybe link referenz). Examplary images of anomalous and good images can be seen in figure x. The structural anomalies consisted of damages to the edge of the part, cut off corners and deep scratches on the surface. Logical anomalies contained missing holes, additional holes and differently sized holes. For simulating missing holes, the holes were stuffed and then the part was spraypainted wholly. Additional holes were simply produced with a drill, likewhise the differently sized holes. The corresponding exemplary masks are also seen in fiure x, as an illustration of how the segmentation of the anomalies was held. If compared with the sample images of figure y(mvtedc loco images) the similarity is visible. The saturation scores for the anomalies, as discussed in section (dataset section loco) were put at (saturation scores) for all above listed anomalies respectively.

- 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

There are multiple approaches to ensembling models in general. When combining a heterogeneous set of classifiers, a common approach is to first calibrate(referenz) and then ensemble each models output (beweis dafür dass das normal ist). There are also approaches to collectively calibrate a heterogeneous ensemble of classifiers while classifying. While performance varies, combining the models is generally not regarded as inherently robust, especially when the classifiers work with features or some other form of representation. This stems from the fact that the model outputs do not necessarily reflect their learned representations(neu formulieren) in detail, which in turn means that you cannot obtain the optimal aspects of each part of the ensemble. A more robust approach would be to ensemble the mentioned feature maps or other representations to in turn train a discriminator for the final classification. To obtain the different feature representations we would use the corresponding training methods of each IAD apporoach and then cut the model of at the respective time. Figures abc show a schematic view of each approachs respective model architecture, together with an indication of where the representations

would be extracted. Proceeding in this way, we would keep all important features of each representation, resulting in a maxmium gain of information and robust predictions over all different classes. Creating such heterogeneous model ensembles on a feature map level was for instance done in (paper ref). Among other results they investigate the performance of heterogeneous models being combined and provide two main approaches to doing so: **General Transformation Block**

- talk about different ensemble approaches we discussed: ensemble model outputs and ensemble model feature maps

feature ensemble: - ground idea: have different algos extract features, and then ensemble them. Afterwards train discriminator on the ensembled features like in simplenet - reference paper that quses PCA and global block transformation - global transformation block: -> resize all feature maps to same dimensions -> append feature maps -> PCA: keep either percentage or set amount

- individual transformation block: -> first apply PCA -> sagen wann das am besten anwendbar ist, auch sagen dass für uns probably der global transformation block reicht -> dann zusammenführen mit resize und appnden

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] K. Roth, L. Pemula, J. Zepeda, B. Scholkopf, T. Brox, and P. Gehler, "Towards total recall in industrial anomaly detection," *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, p. 14318–14328, Jun 2022.

A. Appendix

Appendix here