Ensemble Methods for Visual Anomaly Detection in Manufacturing Settings

Toller Thesis Titel
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Date of submission: April 23, 2024

1. Review: Super Supervisor
Darmstadt

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Darmstadt, 23. April 2024

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List of Abbreviations

Notation	Description
DDPG	Deep Deterministic Policy Gradient
DQN	Deep Q Network
IAD	Image Anomaly Detection
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

Image Anomaly detection as a form of quality control is a widely popular practice in modern manuacturing processes. This also holds true for industrial settings. Ever since the industrial revolution, the need for manufactured metal parts has skyrocketed to a current level of roughly xyz parts of blabla being produced per year(quelle). With rising innovation and production also comes a high need for quality assurance alongside raised standards and requirements. This strict environment(synonym für rahmenbedingungen?) serves among other things to avoid product failure in situations that could cause fatal consequences. Here the quality control in form of anomaly detection often starts at the individual parts manufactured for a single purpose, which demands a large effort and lots of resources due to factors like the named increasing production rate. In earlier days this meant procedures like manual stochastic quality checks of produced parts, a practice that in its nature cannot give complete certainty and requires lots of human labour and thus time and money. Later with the rise of computers and especially sophisticated computer vision methods this process of quality control was more and more being automated using methods like IAD(abkürzung auch erklären wenn in vokabular?), to create a more efficient and easier quality control process. This alongside the striving for even higher reliability and recent developments in artificial intelligence (hier vllt eine refernz für KI geschichte?) brought forth IAD(synonym) as the popular research field that it is today. IAD in our context is a subcategory of general anomaly detection and aims at distinguishing images of a category that conform to some chosen norm from anomalous images of the same category that dont (sollte ich hier eine formel reinpacken? so a la input image i produce score etc). An example would be creating a classifier that is given the image of a screw

and can detect whether or not it conforms to our expectations, which in a manufacturing setting likely means to meet the companies quality standards.
With IAD being a very recent and popular field, there are many different deep learning apporaches that have established themselves over the last couple of years. The best performing ones have generally been unsuperised learning apporaches. This stems from the fact, that in any manufacturing setting, there usually exist far less anomalous parts than regular ones, which creates a significant data imbalance. Moreover it can pose as difficult to actually obtain a large number of data points and great variance, since it is a lot of work to coordinate with adequate manufacturing facilities and also implement the necessary infrastructure to take pictures. This problem is supported by the fact that there are little well established datasets being used for modern IAD research. There are still some credible and widely used datasets, amongst them the MVTecAD [1] dataset acting as some sort of gold standard. The dataset will be discussed in greater detail in the background section. Regarding the kind of anomaly detection models, there is again a great variety of approaches that follow a somewhat different strategy of differentiating between the classes. Still most of them can be categorized with two classes: representation or reconstruction based methods. While representation approaches aim at creating a feature based representation in different forms to then compare the features of new input images, reconstruction based ones try to learn how to recreate the part shown in the image as an anomaly free object, and then comparing the constructed product to the original input. Both workflows are visualized in figure xyz, which showcases the different steps of the respetive methods as described. It is to be said that both approaches offer high quality predictions, yet feature representation methods have more frequently shown in latest research to achieve state of the art results.
The current state of IAD generally consists of very high performing classifiers. Here it is important to differentiate between different applications of those classifiers. There is anomaly detection in form of image classification, which was already mentioned. Furthermore there is anomaly locaization. This describes the process of image segmentation to point out the specific regions in which the deteted anomaly occurs. Lastly besides the applications, one can also categorize kinds of anomalies. The most researched anomaly types are so called structural anomalies, which can be described somwhat as superficial

damages of the parts material or shape, i.e. a strongly bent screw or one that is broken in the middle. Yet recently there has been a new dataset from the creates of MVTecAD that covers logical anomalies, namey the MVTecAD LOCO [2] dataset. Logical anomalies denote ones that violate an abstract set of rules. More concretely this can mean instances like a metal part with an irregular number of holes, or a label missing. Whereas state of the art approaches regurlarly produce performance metrics of up to 99.6% on classification of structural anomalies, they strongly differ in anomaly localization performance. Moreso does the performance plummet when approaching to classify and localize logaical anomalies. Additionally models often show inconsitencies between differnt subtypes of structura and logical anomalies, especially during localization. These inconsitencies and perforance gabs demonstrate that IAD as such is not yet solved and still has a need for improved robustness and generalizability. This need also holds true due to logical anomalies making up an important new domain of automated quality control, as more complex parts could be tested for requirements. Moreover the showcasing of performance inconsistencies between structual and logical anomalies indicate logical anomalies of being a differnt problem domain. Achieving better translation between those domains(synonym) could serve as a basis for tackling other problems in this field that may present themselves in the future(ist der satz inhaltlich gut?)

—- Noch irgendwo erwähnen um notwendigkeit für ensemble zu unterstreichen: oft sind anätze limitiert durch sachen wie pretrained backbones und so ————————————-

1.1. Contributions

This research provides multiple contributions to the field of image anomaly detection, in an effort to further push the progress of robust anomaly localization in differnt domains.

1. To address the problems mentioned at the end of the last section, we attempt (vllt ohne attempt wenn der ansatz funzt) to build a heterogeneous feature level ensemble network, combining differnt state of the art IAD approaches, with the

goal to improve general performance but also robustness in image localization and logical anomaly detection. This ensemble network is then tested on the MVTecAD LOCO dataset to observe its performance regarding both anomaly types.

2. Furtheremore an extensive study on the performance of a wide ranging selection of IDA methods on the MVTecAD LOCO dataset is performed. This serves to highlight the current state of anomaly detection in logical problems, and also investigate the application potential of those approaches in such domains(den satz mag ich nicht). (vllt noch einbauen dass diese experimente ggf noch nie durchgeführt wurden und auch code bereitgestellt wird)

3. Second to last we introduce a new category to the MVTecAD LOCO dataset to further increase the diversity of this dataset and strengthen the focus of this thesis on metal maufactured parts. Many datasets either use synthetic data or images in a very linical setting, therefore this attempt for variance is also a step towards IAD on more realistic datasets.

4. Finally the mentioned network and experiments are also streamlined(checken ob ich das wort richtig benutzt hab) into an easy to use pipeline to be used for future experiments in that area.

The contributions mentioned firstly benefit faster research entry and an accelerated experimentation process, with an intuitive setup, as well as potential industrial applications. Here it is to be mentioned that since the ensemble already is of heterogeneous nature, it is particularly uncomplicated to experiment using various IAD apporaches. Furthermore they give more insight into the capabilities of existing methods in an industrial setting and thus also provide a more various and practical setting than the prior categories in the MVTecAD(referenz) dataset. The same methods are also testet on their limitations regarding logical anomalies which was earlier made out to be a relevant aspect of anomaly detection in current manufacturing quality control settings. 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

presented network can also be used as a foundation for future experiments in different directions. For example, the pipeline may be efficiently used to start investigations on multiperspective datasets in anomaly detection, a topic that also could further advance current IAD applciations.

1.2. Table Test Viz

This is a table:

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

2. Background

2.1. Ensembles

When it comes to ensembling classification models, there are multiple approaches to do so. Many ensembling methods are focussed on combining homogeneous models, meaning a set of related models with similar architecture but different parameters or initializations. Typical methods include (liste an methods mit referenzen, majority vote, boosting, bagging, stacking??, CAWPE, blabla), of which i.e. (ansatz für bäume ensembles) are a typical approach to boost simple classifiers like trees. Homogeneous ensembles are popular, since they tend to boost the performance and robustness of a base classifier without lots of additional work, since the ensemble is normally created by initializing the models in different ways. Heterogeneous classifier ensembles on the other hand are not necessarily combinable that easily, since they usually consist of models with different network architectures. This can lead to results, that should be interpreted as the same, differing by large margins(synonym). Yet ensembles of such variety are often desirable since they offer loads of information from different perspectives or domains when done right. Thus to bridge this gap at the output, a common approach is to first calibrate(referenz) and then ensemble each models output (beweis dafür dass das normal ist). For the last combination step, all ensemble techniques suited for homogeneous ensembling can be applied, due to the outputs being in a comparable state then. There are also approaches to collectively calibrate the hyperparameters of each heterogeneous classifier while classifying(referenz). While performance varies, combining these models

in such a way is not necessarily regarded as the highest achievable robustness, especially when the classifiers work with features or some other form of inner representation. This stems from the fact that the model outputs are merely a small result of larger inner representations that may focus different aspects of information among the inputs. Therefore in turn, you cannot obtain all relevant information that can be offered by simply calibrating the model outputs. A more robust approach to address that problem, would be to ensemble the aforementioned inner representations, i.e. feature maps and in turn train another classifier for the final meaningful output. Another limitation of both kinds of ensembles, being homogeneous and heterogeneous, is that all models have to actually be trained seperately to then utilize the different classification ouputs. This leads to a higher training time and thus also higher computational cost, which is desirable to be reduced in real world manufacturing firms. It should be said that while offering a potential increase in robustness and overall performance, naturally feature level ensemble may also come with certain disadvantages. For instance, it is more difficult to calibrate features from the ensemble members if possible, which may be necessary depending on the nature of the data. An example of our context would be that certain IAD approache project their features into a different space to be effective, making it difficult to ensure that all features are in the same space when dealing with an ensemble. Moreover feature level ensembles also are vulnerable to and reliant on the quality of the input features. This makes the decision on where to cut off the base models very important. The robustness and efficiency has been demonstrated in [3]. The authors utilize a feature level ensemble of multiple convolutional neural networks with different architectures and tasks to improve inference speed and accuracy in plant disease detection. Heller et al.(Heller referenz) show that cutting off several, potentially heterogeneous, classifiers after a couple of network layers and ensembling the resulting feature maps yields firstly a significant improvement in training time compared to classical output ensembles. This stems from the fact, that all base classifiers of the ensemble only have to be trained once for every following training approach. During this the model still stays compact(zitat aus ensemble paper markieren), giving it an memory usage advantage over many supervised approaches. Moreover they compared the performance of different ensemble combinations with conventional output ensembles via the softmax function and reported in all cases no

significant drop in performance. In cases where this approach allowed for different inputs via multispectral cameras(zitat markieren) there even was a similar performance of this ensemble to other state of the art ensembles visible. Keeping in mind the compactness of this new ensemble model combined with an equal performance and possible increased robustness, as argued prior, it is a promising ensemble approach for this work. To obtain ensembled feature maps the paper proposes to bring all feature maps to the same sizes using bilinear interpolation. Since it is not necessarily desirable to keep every available feature map, as this would create inputs with way too many features, the amount of feature maps is reduced using principle component analysis(PCA). This allows for the ensemble to focus only on the most important features, while maintaining an equal amount of maps as if it were composed of a single classifier. To be more specific Heller et al. [3] introduced two different approaches to perform this ensemble. The first is a global transformation block as seen in figure xyz(figure mit global transformation block). Here the features are first all resized to the same dimensions and then connected along their channels through a concatenation layer. Afterwards PCA is applied along the channel dimension to obtain a result with N remaining feature maps, where N can be adjusted for ones needs. This method offers the advantage of efficiency, as PCA is only run once per feature ensembling, and may be applied when there is an almost even number of feature maps per classifier with same input representations(erklärlicher schreiben?). Yet this approach is also prone to a couple disadvantages. If the different input data is collected from fundamentally different sources, there may be a significant loss of information when globally applying PCA. Furthermore this approach cannot be balanced when confronted with classifiers with large discrepancies in channel number. If the amount of feature maps from one classifier completely predominates, there is a high likelihood that most feature maps that are selected are from this classifier, if not all. To combat this at a cost of lesser efficiency Heller et al. also introduced a second approach, namely the independent transformation block, visualized in figure xyz. This procedure is only differing in the sequencing of the actions. Therefore PCA is firstly applied to every set of feature maps, keeping a certain number of feature map components per classifier. They are then all resized to the desired dimensions and concatenated through the concatenation layer. This sequencing allows for maximum information preservation through individual PCA and also to predefine the

number of feature maps to be kept per classifier, preventing larger imbalances.

2.2. Methods of Anomaly detection

Over the last years a great amount of different approaches to solving IAD have been published. In order to compare different anomaly detection methods, categorizing them with respect to different aspects serves a better comparative analysis in regards of strengths and weaknesses. It also helps gain a better understanding of the different approaches in the global IAD context and is useful detect possible patterns in performance correlated to categories. This obviously also holds true for IAD approaches. Survey papers like (namen nennen) [4] [5] primarily compare but also categorize IAD approaches, leading to the conclusion that there are effective and generally applicable ways to group certain approaches, as visualized in Figure xyz. Here it has to be said that the following categorizations naturally are a generalization, as there may be different niche settings or even approaches who combine multiple categories.
The first distinction relevant to our work is between supervised and unsupervised settings. Current deep learning approaches that have established themselves as state of the art in image anomaly detection are almost exclusively unsupervised approaches. This partially stems from the fact that in practical situations, 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 sites nowadays. Therefore if one were to consider using a classical supervised learning approach to detect anomalies, either a strong class imbalance or a nonrepresentative class distribution would constitute a problem. While there are some solutions for this, they often either do not suffice for imbalances of this magnitude or far to resource extensive. To overcome these issues, some supervised approaches [6] operate in a few-shot setting which limit the training data amount needed for proper training. Nevertheless as the focus on unsupervised IAD methods in current research persists, this work will also restrict itself to such approaches. This also facilitates the execution of the ensemble approach presented in chapter 4(methods).
Looking into the unsupervised anomaly setting, the next important distinction is between

reconstruction based approaches and representation based ones. They differ in the sense, that the former are comparing the distances between two images and the latter measure distances between feature representations.
Reconstruction approaches first learn to reconstruct the objects given in the input images. This is done by feeding the network normal train data, aswell as noisy data. Noisy data are are which are altered by methods like gaussian noise(rephrase), although the exact noise application is depending on the specific approach. During testing, after having successfully learnt to reconstruct anomaly free images, the method is then given an input image, reconstructs it and compares both images using some sort of distance measure. This process is also depicted in figure xyz. Representation approaches on the other hand use feature embedding methods to obtain feature representations of images and compare those. As shown in figure xyz, during training the model is learning to correctly extract features of input images. When given an anomalous sample during testing, the model then also extracts the features from the input data and compares those to its prior feature level representations of the class object. A decision is then made aswell using a distance measure. Both classes of IAD methods have shown to produce state of the art results. Yet currently more approaches are representation based [5] as they have shown SOTA performance more consistently. Nevertheless it is reasonable to focus on both kinds of IAD, as they may excel at different regions of anomaly detection and evaluation criteria. Namely reconstruction methods are often showing a better performance at pixel level anomaly detection in comparison to feature embedding/representation methods, as their principle is based on pixelwise comparisons of input and reconstructed data.
Again, looking at the representation based approaches, some distinctions can be made on exactly how the method implements a representation based procedure. The main approaches in this category are ones featuring a memory bank, teacher-student architecture, distribution map and ones employ a one-class classification strategy. The characteristics of each strategy are visualized in figure xyz. The subcategory of memory bank denotes the procedure to store feature representations, that are extracted from training images, into a data collection structure. This structure is then used to compare new features from input images to the stored ones to form a decision. Memory bank approaches offer the upside of little training time and quick construction, yet the usually suffer from high

memory usage and costly inference, due to the feature representations being stored into memory. Some papers have addressed this problem. Famously patchcore [7] introduced a coreset-subsampled memory bank, greatly improving on said bottlenecks and setting precedent for more efficient memory bank approaches. Teacher-student architectures reference the use of two networks for anomaly detection. This architecture has also been one of the more effective ones and its performance greatly depends on factors like the selection of the teacher model and way of knowledge transfer between the two networks. Here the teacher model is usually a pretrained backbone, that transfers knowledge onto the student model during training time, whereas the student model is simultaneously learning representations from the teacher model aswell as learning how to represent the input data by itself. During testing, the extracted features of teacher and student are compared, which would then be similar for normal images but have larger differences when presented an anomalous data point. Next, distribution map approaches try to map the features from their original distribution into a more suitable one. This vastly facilitates a identification of anomalous features as shown in figure xyz. Such an approach requires a method to map the features between distributions. Often times a variation of normalizing flow is utilized for this [5]. Normalizing flows as a class of generative models [8] are advantageous for transforming probability distributions because they provide a flexible framework to model complex distributions and efficient sampling. This enables accurate distribution mapping aswell as sampling. Lastly, one-class classificaiton is somewhat similar to a distribution mapping approach. The key difference is that the latter maps features into a desired distribution and the former focusses on finding boundaries between normal and anomalous features. To efficiently do that, features are projected into a suited space using a network. To learn an accurate boundary, the approaches generate fake anomalous features to then differentiate from normal ones. This method greatly relys on the the quality of generated features and as such may be variyngly effective. A typical approach for generating fake samples in this works context is with the use of gaussian noise [9].
Circling back to reconstruction based methods, they also can be parted into subcategories. Here the most predominating one is the use of autoencoders to obtain a generated image. Many reconstruction approaches make use of typical AE encoder and decoder structures. They are mainly seperated by the method of resolving differences between the input image

and the reconstructed one. While there are too many difference evaluation approaches to name, DRAEM [10] can be named here as one of the most famous reconstruction autoencoder approaches. It uses the output of the reconstructive network in combination with the original image as the input for a discriminative subnetwork and achieves very good results and demonstrated a nearly equal effectiveness of reconstruction based methods to representation based ones.(nachteile von DRAEM/AE nennen) Another, albeit less popular, approach in this category would be the use of GAN architectures/concepts to try and solve the detection problem. While we don't cover the basic principles of GANs in this chapter, GANs applied in IAD may still suffer the same disadvantages of regular ones, which include training instability, high computational demand and a higher difficulty of correct training and evaluation. Hence the use of GANs for IAD is not commonly seen, although the nature of them may promise more realistic and higher quality training data than other approaches. Another kind of reconstruction based IAD involves the use of transformer structures. They allow for good caputiring of spatial relationships and long distance feature extraction [11], making them useful for not only structural but also logical anomaly detection. Papers like [12] make use of transformers for feature reconstruction and as they are very limited in reconstructing anomalous features well, making for an easy distinction. They show in their experiments that their approach ADTR is able to outperform all shown baselines, including a variety of different autoencoder apporoaches. Finally there also exists an approach that has been gaining popularity lately: the usage of the diffuion model [13]. Papers like [14] leverage the models ability to capture complex dependencies to detect anomalies in IAD, and other papers [15] further improved its efficiency by speeding up the denoising process.
After carefully categorizing the important classes of unsupervised IAD, it is now discernible how many different approaches towards anomaly detection exist, and may yield differnt merits. Below(maybe sections auzählen/zitieren?) we further elaborate on a few select IAD approaches from different categories who were utilized for the MVTecAD LOCO performance analysis or the ensemble model.

2.3. Datasets

The datasets used in image anomaly detection are scarce, especially when it comes to anomaly detection in a manufacturing setting. There are many datsets and approaches that specialize on certain materials [16] [17] [18] and often only one classs. What currently stands out as a gold standard among IAD datasets is the MVTecAD [1] dataset. The authors created it as a highly representative and standardized set of anomalous images along with training images. It has 15 classes from capsules to screws. Moreover the dataset 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 image labels are given through its folder structure. Its paradigmatic structure tree can be seen in figure xy. As shown, each class contain train images, which only consist of regular examples, and test images. The data among the testing images is categorized by a title describing the anomaly. The ground truth folder contains according ground truths on a pixel level. Example images of the dataset are to be seen in figure z. They typically are of a rectangular shape and their resolutions range from (pixel min) to (pixel max). More specifications can be found in Bergmann et al. [1] and the whole dataset is publicly available at the official website[19].
The MVTecAD(referenz) dataset is regarded highly among IAD papers, and has since its introduction been used in most relevant papers as a dataaset to benchmark the respective approaches on. This is also likely to remain the trend, since many state of the art 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 highest performance holding approaches. Despite this work focussing on manufacturing settings MVTecAD is one of only two datasets relevant to this work, and serves as a comparison for the performance investigation of this papers approaches on the second dataset. This is mainly due to the dataset's importance and its relation to the second dataset.
Later in 2022 Bergman et al. has introduced another IAD dataset that is loosely related to their original MVTecAD dataset, namely the MVTecAD LOCO dataset [2]. This dataset works with the same ground ideas as their original MVTecAD set, but extends the con-

ceptual contents of the dataset by logical anomalies(neu formulieren das klingt scheiße). It consists of five classes: breakfast box, juice bottle, pushpins, screw bag and splicing connectors. 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. As mentioned in the introduction structural anomalies are visible damages to the objects, similar to the MVTecAD dataset. Logical anomalies denote violations against arbitrary restrictions imposed by the authors. 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 more than one pushpin, it would constitute a logical anomaly. If on the other hand a pushpin would have a crooked or broken tip, it would be labelled a structural anomaly. Structurally the differences of the MVTecAD and the MVTecAD LOCO dataset can be seen when comparing figures a and b, which showcases the anomaly classification, aswell as the method of storing segmentations. Here there eixists an image file for each anomalous ground truth area, which are mapped to the image by the folder name they are in. Lastly there exists a validation set in this dataset,
The addition of logical constraints opened an interesting area of research, since the high performance of current state of the art 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. Another concept introduced in [2] is the saturated per-region overlap score, also sPRO. The metric is further analysed in setion (metrics section), but in short gives a measure on how well two regions overlap, while also accounting for regions overlapping in a way, that is seen as sufficient. The criterion of sufficiency is given by a file in the respective class, which maps a saturation score to each kind of anomaly. Bergmann et al.[2] lastly also released a new IAD model together with the new dataset. The model uses autoencoders(bissi besser beschreiben hier). Since the source code has not been made public, this work refrains from using the method proposed in the paper.

2.4. Model Calibration

Calibration or rather confidence calibration is the process of adjusting/scaling your models ouput so that it indicates how likely it is to be correct. This is an important action, as nowadays models demonstrate increasingly good performance, scoring very high accuracies on classification tasks. Models that show to be correct that often, generally also have porential to be deployed in real world use cases, which especially holds true in IAD research for manufacturing contents. [20] reports that most modern neural networks are poorly calibrated in regard to their confidence. Current IAD methods investigated in this work confirm this, only returning anomaly scores devoid of any confidence indication. Correct confidence calibration can help evaluate models using new metrics, increase the users trust into the application and also help to decide on how to utilize the predictions of the model in ones context [21].
[20] review multiple promising ways to calibrate the confidence of a model. On a top level, the authors distinguish between calibrating binary classification models and multiclass ones. For binary models they present histogram binning, isotonic regression, bayesian binning into quantiles (BBQ) and lastly platt scaling. Histogram binning is a non-parametric approach and involves binning the uncalibrated prediction possibilities into distinct bins. Each bin B_m is then assigned a confidence score θ_m. During test time the models prediction probability $\hat{p}_i$ is mapped the score θ_m of the bin B_m it falls into, resulting in a calibrated confidence $\hat{q}_m = \theta_m$. The boundaries of the bins are here chosen so that they minimize the bin-wise squared loss in accord to:

2.5. Metrics

Metrics are known to be an important part of developing any artificial intelligence related models. Many of them are used to infer different characteristics of model performance and should be used in different appropriate circumstances, depending on which aspect is important for the current application. Therefore, before the actual developing, one must

first choose appropriate metrics to optimize and evaluate on later. IAD as a research area themselves has certain metrics that are the main performance evaluation tool across most papers. A collection of different metrics in this domain are displayed in table 1.1, which is taken from [5]. Visible are well known ones from many other machine learning models like precision, recall, TPR, FPR and the F1-Score. These are generally applicable in most cases, but are not listed in any recent important papers and thus are not important for any analyses in this work. The other metrics are more IAD specific. By a large margin, the most important scoring standard is the AUROC. This metric is usually referenced for image level binary classification and gives an indication on how good the model is able to distinguish between both classes. Its calculation can be seein in table 1.1. Moreover it can be used on a pixel level, which is also a popular approach but not utilized everywhere. Next in importance is the per-region overlap(PRO) score or also the area under the PRO score(AU-PRO). This metric denotes the per-region overlap of two areas on a pixel level and can be calculated using (PRO formel hier hin, im satz rechts dann ggf bezug auf formel zeichen nehmen). The two areas compared are generally an image mask and the according segmentation by the model. The AU-PRO is then calculated by plotting the PRO score at different threholds for the segmentations, and reporting the area under the curve. This can be used to rate the segmentation performance of different models and is also a frequently featured metric in IAD related research. Related to this score is the saturated per-region overlap (sPRO) and also the according are under the curve, the AU-sPRO. This metric was introduced in [2] and briefly mentioned in section (dataset section). The method of deriving the sPRO score is shown again in equation abc, where m denotes the amount of anomalous regions in an image, $A_i|i \in \{1, ..., m\}$ an anomalous region among them and $s_i|i \in \{1, ..., m\}$ a respective saturation threshold. P is considered to be the pixels classified as anomalous in the target image. The sPRO score is the calculated by averaging the intersections of all predictions and ground truths of an image, while norming the values by the saturation threshold and proividing an upper limit of 1 per region. It is to be said that this gives a similar view on the segmentation performance as the PRO score, as it is a generalized form of it and can producet the same results if the saturation threshold would be equal to the amount of anomalous pixels per region. However, due to its cap of 1, it also rates differently large segmentations equally in cases

where the anomalous position posesses some uncertainty. Figure xy demonstrates this behaviour in the case of a logical anomaly of the pushpin class. As visible, the logical anomaly consists of an empty pushpin compartment. The missing pushpin could be placed in any place of this smaller box for it to be valid, therefore an amount of pixels equal to the amount a visual pushpin posesses would suffice. Yet the conventional PRO score would keep on rising as the segmented area gets larger within the anomalous region. Due to the saturation score and limit. this is prevented by the sPRO metric as figure xy shows it to be already saturated once the minimum required amount of pixels is achieved. The saturation scores for each anomaly have to be individually set for each anomaly, and are given for the five classes of MVTecAD LOCO [2].

2.6. Anomaly Detection Methods

In this section we further dive into some of the IAD approaches that can be viewed as class representative to some extent. All following methods have demonstrated SOTA performance in at least some categories and are participants/candidates/(synonyms) in the performance study on the MVTecAD LOCO dataset. In the this work we investigated the most widely popular categories of IAD, namely memory bank, one-class classification, teacher-student, distribution maps, autoencoders and diffusion models.

2.6.1. PatchCore

As the memory bank approach patchcore [7] has been chosen. It has demonstrated very high accuracy in both image and pixel level anomaly detection and set a high standard for performance after its release. The fundemental principle of patchcore is visualized in figure 2.1 and is according to the basic memory bank principle. First a pretrained feature extractor is used to retreive features of the input data. Next in this paper, the features are turned into locally aware feature patches, meaning the feature maps are cut into small fields and applied preprocessing operations like pooling to ensure the

patches to be locally aware and also of similar dimension throughout the training. This results in patches that adhere to equation(patchcore patch equation benutztne). The effectiveness of this patchwise approach is justified with each patch, despite being small, having a large enough receptive field size to provide a meaningful anomalous context when learned. Before commiting the resulting patches to the memory bank, patchcore first induces coreset subsampling on the set of feature vecotrs. This ensures a reasonably small memory bank size that is large enough to offer good results, and yet is not to time and memory consuming when performing nearest neighbor search. As a memory bank structure, patchcore utilizes a search index by FaissNN(referenz) which offers the application of kNN with great speed, performance and even a desired tradeoff if necessary for a task. Since performance is the main criterion in IAD research though, this tradeoff is not utilized.

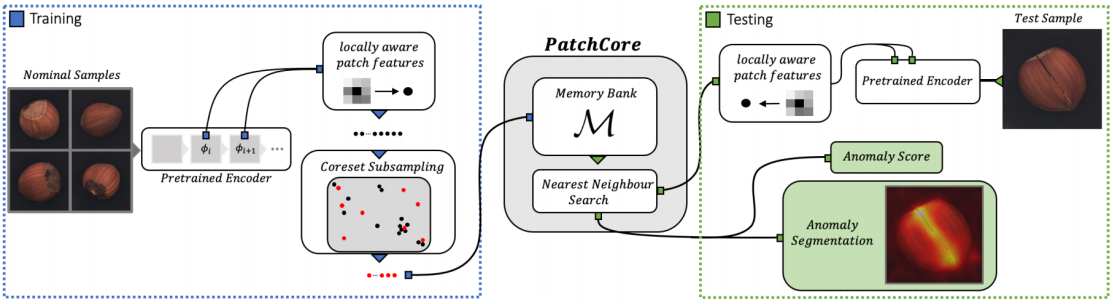

Figure 2.1.: Hier korrekt zitieren

At test time, the input images are processed exactly like the training images were, and afterwards the model searches for the nearest neighbor of each patch, and calculates a distance measument as in equation xyz: The distance scores are then used twofold: The maximum distance indicates the anomaly score on an image level, while the patchwise distances are reshaped, interpolatesd and smoothed to a segmentation map for pixelwise anomaly detection.
Patchcore has greatly improved the status of prior thought slow and rarther inefficient memory bank approaches throough its subsampling approach. It moreover offers to train

a model with little time since the only training that is really done is to fit the memory bank structure with patch vectors. Besides low training time it also requires low storage cost and offers very high and state of the art performance that can also be boosted using simple majority voting(checken obs nicht doch averaging war) ensembles in its paper. Yet due to its nature as a representation based approach, patchcores efficiency is limited by the the pretrained feature extractors acting as its backbones. This problem persists but is also approached by the paper, as they offer a implementation to train the backbone extractor alongside the actual training.

2.6.2. SimpleNet

Notizen für simpenet/sachen die ich sagen will:

- simplenet ist auch representation based aber ein feature projection approach(factchecken!!)
- erklären was das heißt, zb dass die features in eine bestimmte dimension projected werden um aussagekräftiger zu sein - published as easy to use and application friendly approach by blabla

- simplenet pipeline: -> training: -> features werden auch hier mit pretrained backbones extracted und wie bei patchcore zu locally aware patches gemacht -> features werden projected wobei die projection auch erlernt wird(sagen dass single layer network genügt hierfür) -> fake features werden generiert. simplenet disst hier die bisherigen ansätze von synthetischer data(referenzen) und schwört auf gaussian noise -> fake features sind dann richtige features + gaussian noise -> discriminator: 2 layer MLP, kept very simple -> features are appended and all batch is fed to discriminator per epoch -> discriminator then learns on them -> loss beschreiben auch mit formel -> discriminator spuckt werte aus(scoring formel zeigen) -> anomaly map ist discriminator pro patch, hochinterpoliert, image score ist höchster map score

Leistung von simpenet: - sehr gute results, auroc und pro bitte raussuchen - geschwindigkeit vergleichsweise langsamer als zb patchcore und padim welche representation based sind

aber auch langsamer als reconstruction based DRAEM -> around 79 FPS für simplenet und nur ca 10 für patchcore und ca 67 für DRAEM

2.6.3. AST

2.6.4. DRAEM

2.6.5. RevDist

2.6.6. CSFlow

3. Related Work

4. Method

4.1. Calibration

- say that IAD methods only give anomaly score that is not saying anything relevant regarding confidence - cite [22] that says that well calibrated ensemble members do not need to yield calibrated output

4.2. Discriminator

Our approach to use a small, compact discriminator to differentiate between regular and anomalous image features is inspired by the approach presented in SimpleNet [9]. Since the discriminators inputs in the ensemble pipeline will be of the same nature as the inputs for SimpleNet's discriminator, it is reasonable to utilize their network architeture for this work. Looking back at section (simplenet section) and moreso figure xyz(simplenet architecture), we thus will adapt the SimpleNet pipeline after the feature adapter step. This means the discriminator, shown as the labelled circle will conceptualy be equal to ours. Instead of the merely adpated features, the ensembled features from section (ensemble feature section from methdos) will substitute. The artificial anomalous features, depicted as the red tiled pane in the figure will also be provided during training time. Here we also adapt SimpleNet's approach of gaussian noise for producing those artificial

features. (satz ob wir mit simplex noise arbeiten wenn ja dann erwähnen) As also stated in SimpleNet (googlen wie man wörtliche Zitate korrekt benutzt), this discriminator "works as a normality scorer [...] estimating the normality at each location (h, w)". Moreover are positive and negative outputs expected for regular and anomalous features respectively. As to the discriminator network specifics, a regular "two-layer multi-layer perceptron"(zitat markieren) is used. As optimizer a regular adam optiizer by pytorch with a learn rate of (werte erst sauber aufschreiben bevor ich es hier hinschreibe)

- say that this is the binary discriminator for detcting the anomalies from ensembled feature maps - repeat that this is largely based of simplenets discriminator - describe model architecture as described in simplenet paper - list parameters from code like optimizer, learn rate, epochs, etc. - also describe loss

4.3. Flat Connector Class

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

4.4. pipeline

- explain brief structure of the pipeline - ???

4.5. 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

4.6. Different ensemble approaches

- weighted, random forest etc - specifics

4.7. Logical Anomaly Detection Using Conventional Approaches

As discussed in the introduction section(1), logical anomalies represent a signifacant part of image anomaly detection in modern manufacturing settings. The experiments also serve as an extensive comparison of SOTA methods for IAD versus recent approches that where introduced with special mind to logical anomalies, like GCAD [2](GCAD reference von Paul Bergmann). Moreover, for a qualitative evaluation of the performance change when using feature level ensembles, one first needs to evaluate the base performance of each relevant classifier of the set. Hence this work features experiments to evaluate IAD approaches mainly evaluated on the classical MVTecAD dataset. To do so, the original code from each paper was taken and not modified in regards to any reportet parameters and/or arguments. This was to prevent possible unwanted deviations in original performance by changing up synergies. This paper recognizes the possibility of improved performances on the logical anomalies dataset with different combinations of model parameters. Yet this work focusses on the performance(synonym) of current unmodified apporoaches and more importantly the increased robustness through the use of ensembles. Therefore research regarding this hypothetical improvement would have to be done in another work. Metrics that are specifically looked at in this context are the AUROC, pixel AUROC(weitere maybe einfpgen) and the sPRO. If the functionality to evaluate these metrics was already given, the results of inference were (übernommen), else the according functionality was implemented in this work and used to produce the according metrics. Papers whose approaches were evaluated using the MVTecAD LOCO dataset were: SimpleNet [9], PatchCore [7] (list of paper references with names). These papers were discussed in depth in the backgrounds section and any specifics like hyperparameters can be viewed in the corresponding paper. Furthermore all named classifiers were including, among other variable measures, a preprocessing step to resize the input image. This makes for a variable model input and also the ability to process rectangular images, which is important due to MVTecAD LOCO images being rectangular unlike the squared input from the standard MVTecAD dataset. The only necessary modification to the whole process of anomaly detection was the generation of image masks. The MVTecAD LOCO dataset

stores its masks in multiple seperate black and white images, one for each individual anomaly. To fix errors stemming from this fact, additional code was added that pastes all masks belonging to one image into a single mask before iterating through the data.

Überschrift reformulieren!

What i wanna say in this section: - what we did to do the survey on LOCO IAD detection - what we did to the methods(nothing) - aspekte anhand welcher wir die experimente analyiert haben

- wenn ich es actually auch mache dann ablation experiments nennen in welchen ich die images square

5. Experimental Setup

- get information from cluster what it is running on etc. - look in other papers for how they did it -> ensemble paper did this section but also look in IAD papers

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

6.1. SOTA Methods Performance on classical LOCO Dataset

In this section we review the performance of prior introduced anomaly detection methods. All experiments were performed with the same experimental setup as explained in section (referenz of experimental setup section), the conditions explained in section (referenz von methods section über loco) and on the mvtec LOCO dataset [2]. The results of inference on the test set can be seen in table x (tabelle mit ergebnissen). As it can be seen, all models scored a significantly lower result on the MVTecAD LOCO dataset than on the normal MVTecAD one(exemplary scores seen in table xy(table mit normalen mvtec scores)). A lower performance is generally to be expected, since firstly logial anomalies are regarded as a more difficult problem than structual ones and secondly the average SOTA performances as seen in table x(tabelle mit ergebnissen) is already closing in on an AUROC of of 1. (den satz rechts von hier müsste man maybe rausmachen oder umschreiben)Therefore there is not much room for further improvement in similar settings, and a worse performance still aknowledgeable as very good. Yet there is an drop in cross-model average AUROC of approcimately (durchschnitts drop ausrechnen), which is a remarkable(synonym)

difference. Most other metrics, namely (metrics names), also declined with an respective average of (respective averages). As explained in section (referenz zu metrics section von background), the sPRO (or rather AU-sPRO) was a score introduced in [2] to gain an advanced insight on the quality of segmentations. This means that all approaches who either were published before or did not include this paper in their research likely did not include this metric, which holds true for the approahces used for this experiment. Therefore no comparison in sPRO/AU-sPRO can be shown(vllt einfach spro auch für allte ansätze implementieren?? dann kann ich den satz ändern). Comparing the sPRO scores of the SOTA methods in this experiment with the ones from compared to GCAD [2] shows asignificantly (abchecken ob wirklich) worse performance. Among the different models, the highest scoring one was PatchCore [7]. It scored an average (metrics einfügen) feature embedding based approaches like achieved the highest scoring

Interpretation of results hier, weiß nicht in welche section das eigentlich muss:

6.2. Ensemble Performance

Notizen für diese section: - hier soll reportet werden wie das ensemble sich geschlagen hat - dazu brauche ich: -> metriken(AUROC sPRO und vllt pixel auroc) von dem ensemble auf flat connector + mvtec loco -> beispielhafte segmentierungen -> plots von loss und auroc über training

- drauf eingehen wo sich das ensemble wie gut geschlagen hat -> vergleich mit patchcore und simplenet wichtig, gerne auch mit DRAEM vergleichen als reconstruction representativer algo -> sagen bei welchen klassen es gut und nicht so gut geklappt hat, vergleichen mit ergebnissen aus LOCO studie oben drüber(vllt in conclusion?) -> mehr images in appendix anbieten

7. Conclusion and Future work

7.1. Ensemble Network

7.2. SOTA performance

7.3. Flat connector

7.4. Outlook

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A. Appendix

Appendix here