Evaluation of Unsupervised Methods for real-time Anomaly Detection on Textile Surfaces

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Motivation

Anomaly detection methods show great potential in the context of industrial quality inspection. Specifically, defects in fabric surface structure lead to significant reduction of revenue. Thus, it is in both the economic and ecological interest to reliably detect existing abnormalities early on to stop the machine and prevent further spreading. Given the drawbacks of manual inspection, there is a strong demand for dependable, precise and swift surface defect detection systems to reduce fabric wastage and improve production efficiency. Unsupervised methods, a focal point in computer vision research, solely require non-anomalous data samples for parameter optimization. With no prior information in the form of labels, models learn inherent data patterns during training, allowing them to detect deviations from these patterns as anomalies during testing. In contrast, traditional supervised algorithms pose practical limitations due to their reliance on time- and resource-intensive data collection and annotation, illustrated in the following figure 1.

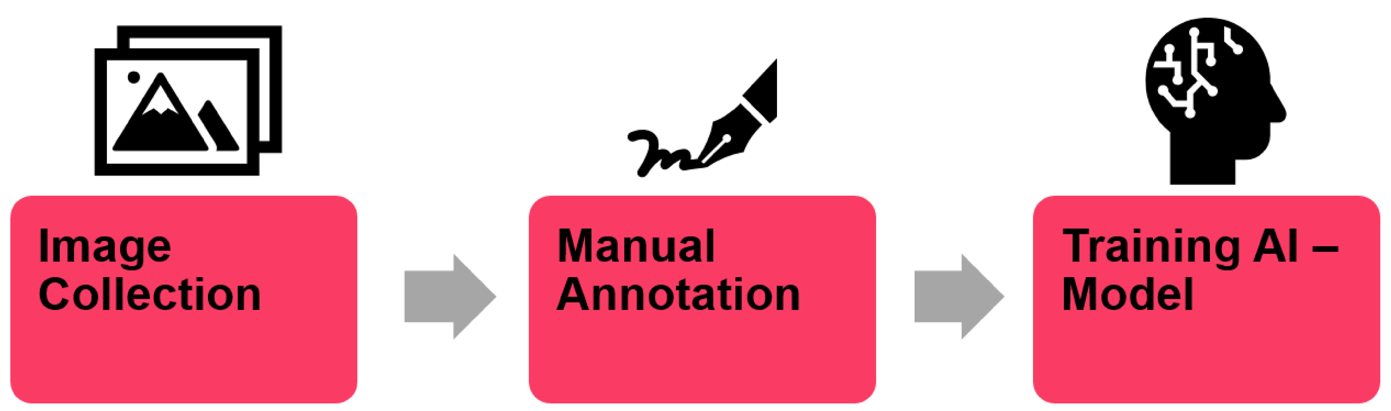

Figure 1. Basic model development process for supervised methods

As defects or anomalies occur infrequently in textile manufacturing, it is challenging to gather a sufficient quantity of anomalous data, which leads to imbalanced datasets. In addition, manual labeling is an extensive and tedious process, which must be repeated for every new application involving different fabric surfaces or machine types. Moreover, supervised models can only recognize known defects, which are represented in the training set, lacking the ability to identify new and unseen anomalies.
Many promising unsupervised anomaly detection methods have been proposed in the literature to address these practical limitations of supervised learning algorithms. However, their performance is typically evaluated on academic datasets like MVTec [2] or VisA. It remains unclear whether their success translates effectively to the specific real-world application of fabric defects.

Research Questions

To address this gap, this thesis explores state-of-the-art unsupervised methods applied to image data for real-time defect detection and localization on textile surfaces with the aim to answer the following research questions.

1. Which state-of-the-art unsupervised anomaly detection methods are suited for real-time defect detection on fabric image data?
2. Which algorithm performs best for the given scenario of real-time defect detection and localization on textiles?
3. Can these models achieve comparable performance to the currently employed supervised method while requiring less prior information and offering significant advantages during the data collection and training process?

Methodology

The following state-of-the-art unsupervised methods are applied to anomaly detection and localization on fabric image data utilizing the in figure 2 depicted framework:

Table 1. Unsupervised methods for anomaly detection

Reconstruction-based	Representation-based
CFlow [5]	*CFA* [6]
CSFlow [7]	*PaDiM* [3]
FastFlow [10]	*Reverse Distillation* [4]
DRÆM [11]	*STFPM* [9]

A representative dataset of defect-free fabric images is collected to train the methods using implementations of the open-source python framework *Anomalib* to detect common fabric defects. Their predictive performance on holdout data with normal and anomalous samples is analyzed for defect detection on both image- and pixel-level using different preprocessing approaches such as machine part segmentation. Furthermore, the unsupervised methods are directly benchmarked in speed and accuracy against a well established supervised solution to the problem.

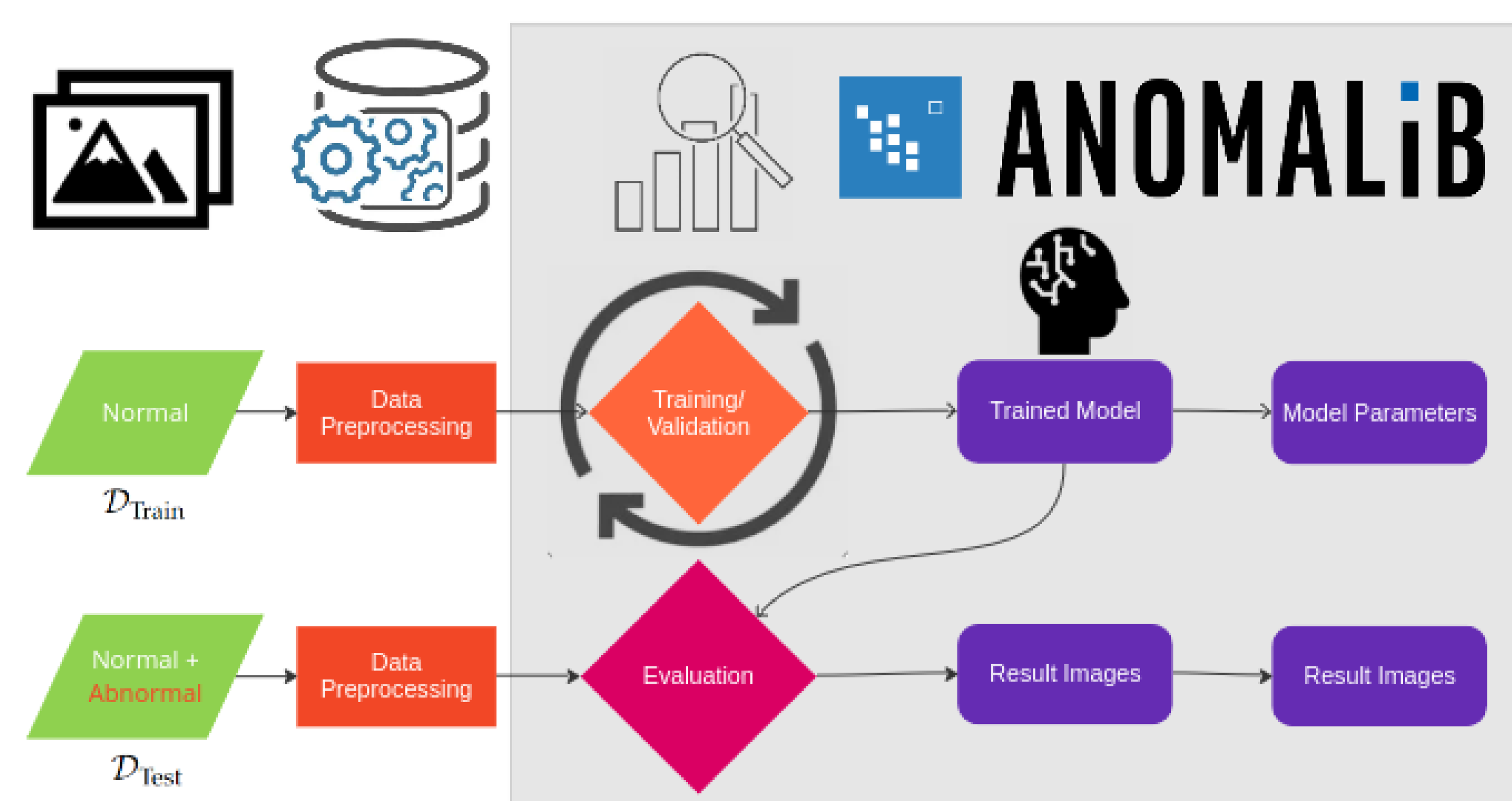

Figure 2. Training and evaluation framework

Anomaly Detection Results

The experimental results on anomaly detection measured with the AUROC metric indicate that the methods *FastFlow*, *PaDiM* and *STFPM* achieve highest classification performance on the presence of an anomaly in the image with lowest runtime.

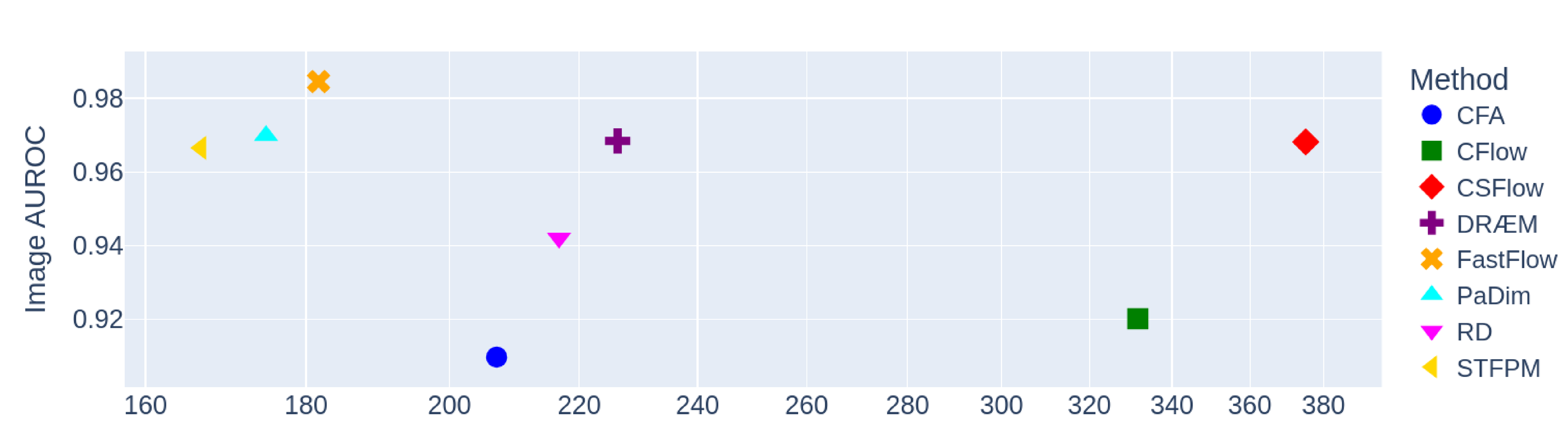

Figure 3. Image-level AUROC plotted against inference time per method

Anomaly Localization Results

For anomaly localization in the images, the methods *DRÆM* and *FastFlow* provide the best defect segmentation masks suggested by Dice Coefficient.

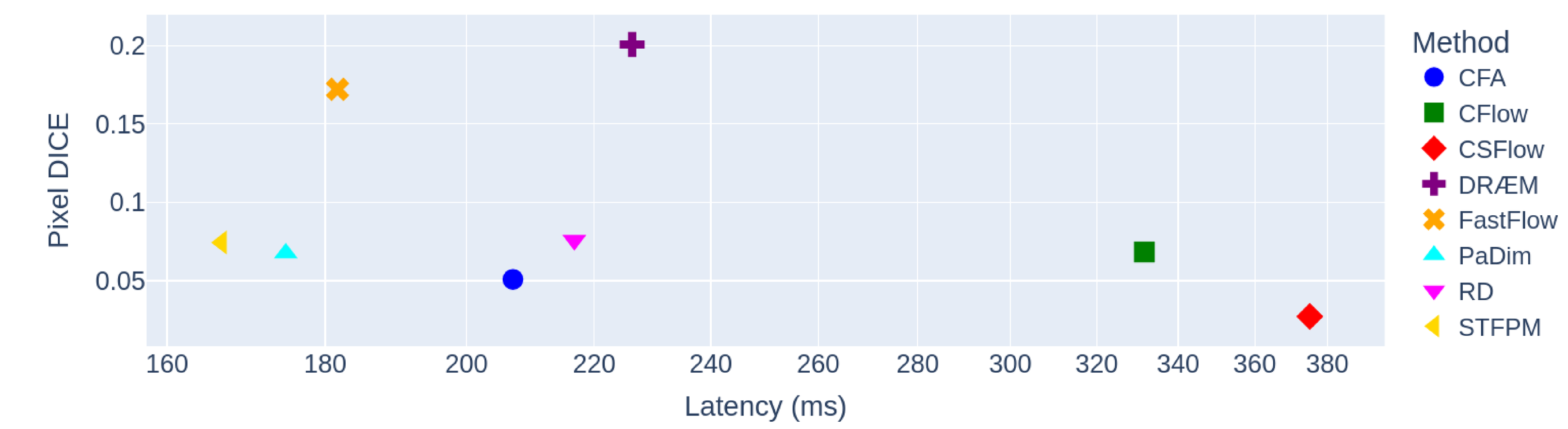

Figure 4. Pixel-level Dice Coefficient plotted against inference time per method

Conclusion

The conducted experiments indicate that recently proposed anomaly detection methods achieve impressive classification peformance, with AUROC scores as high as 98.5%. Additionally, solid anomaly localization results were reached, which could be improved with higher input resolution. Particularly, the method *FastFlow* yields competitive results, outperforming the supervised model in terms of precision and specificity, despite significantly higher computational complexity. Therefore, unsupervised methods were successfully identified as promising alternatives for supervised approaches for anomaly detection. They enable faster and more cost-effective model development, significantly enhancing application capabilities within industrial environments.

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