ARTIFICIAL INTELLIGENCE FOR ANOMALY DETECTION IN VISUAL QUALITY INSPECTION OF ROTARY SCREEN PRINTING

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Abstract

Problem statement

Modern rotary screen-printing machines print fabrics with a speed of appr. 50 m/min. During the process, errors often occur due to fluff suspended in the air that settles on the rollers and blocks the pores, preventing ink from being transferred to the fabric. This creates inkless spots of fabric that are smaller than 1mm and barely visible to the human eye, especially in complex patterns.

Due to the small dimension of errors and high speed of the printing process, the detection of errors is challenging and often only possible in the final quality inspection after the fabric was finished. This leads to a high amount of textile waste and extra time consumption for reworking.

Approach

To speed up and improve the quality inspection process on the screen printing machines, this work proposes the combination of cameras with artificial intelligence to carry out quality inspection tasks.

Common approaches for quality inspection and error detection with image processing include the supervised training of classification models. However, with ever increasing product catalogs and with the wide variety of sizes and shapes that errors can take in rotary screen-printing processes, managing datasets large enough to reach a reliable accuracy might prove challenging to achieve generality of a model. On the other side, unsupervised learning models can be used for the simpler task of detecting anomalies, and with a proper training pipeline, the requirements for dataset sizes and training times can be significantly reduced.

This work explores the use of unsupervised generative models for anomaly detection in a rotary screen-printing process, by using the reconstruction error, i.e. the difference between the input and the generated output, as a measurement to detect outliers, while keeping the training dataset as small possible. The tests were carried out with samples of the rotary screen-printing process of the company E. Schellenberg Textildruck AG, Switzerland. Pictures of 5 types of printed fabrics were captured with 1D and 2D cameras to train and validate different model architectures.

Result and conclusion

Our results show a ~90% detection accuracy in most of the samples on a lab scale using our developed generative AI model. Further research is done on the influence of the environment in the printing process such as vibration, speed, and light refraction.

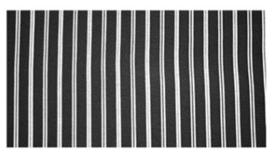
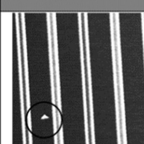
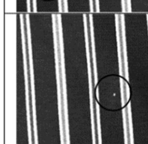
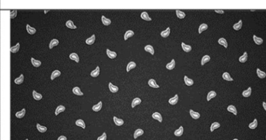
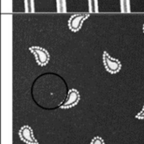
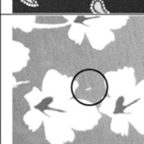
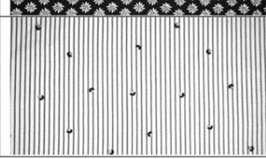
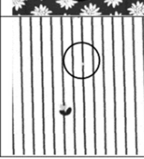
Introduction

Contemporary rotary screen-printing machines achieve a printing velocity of around 50 meters per minute. Throughout this operation, challenges frequently arise from airborne fluff that settles on the rollers, obstructing the pores and impeding the ink transfer to the fabric. Consequently, tiny inkless areas on the fabric, measuring less than 1mm and hardly perceptible to the human eye, manifest, particularly within intricate patterns.

The resources required for manual quality control are in poor proportion to the good quality of the finished textiles. Fundamentally, this problem cannot be excluded for printed and dyed knitted and woven fabrics. A defective printed textile surface of insufficient quality can only be detected by considerable additional effort in the running process. These errors necessitate 100 to 200 manhours per week to rectify.

Quality control in textile printing companies is mainly carried out by means of classical visual inspection. The existing high error rate of visual inspection of more than 65% provokes a considerable amount of rejects and simultaneously entails a high use of resources. At the same time, costs are rising significantly and customer satisfaction is steadily declining.

Table 1 investigated errors in printed textiles with a size of 1 - 4 mm

	Total view	Error	Error size
Fabric 1			4 mm
			1 mm
Fabric 2			1 mm
Fabric 3			3 mm
Fabric 4			3 mm
Fabric 5			2 mm

At present the market offers several automatic quality inspection systems for various surfaces, such as paper, metal and also for textiles. Nevertheless, the printing process is a particularly high challenge due to the variation of patterns, the process speed and other parameters (vibration, light conditions, dust etc.). Two types of inspection systems can be distinguished:

- Systems with error classification
- Systems with anomaly detection

Quality inspection systems with error classification are dependent on a huge number of existing images of errors. The user must classify all upcoming errors to train the system, which results in high cost for the training phase for each new pattern.

Whereas an inspection system with anomaly detection refers to a at least one master image of a correct printed textile and compares the master with the recorded images of the running process. Consequently, unlike the error classification, a large amount of error images is not necessary. Fundamentally, an anomaly can be called rare events, deviations or outliers. Existing data sets that do not match the main distribution are declared as such. According to Barnett and Lewis, the following definition can be formulated: "...an observation (or subset of observations) that appears to be inconsistent with the rest of the data set." [Fre95]

Within this work anomaly detection was chosen over classification because the situation in the production environment required to know only if errors were happening, not which ones. The aim of this work is to develop a neural network for the detection of anomalies in defectively printed woven and knitted fabrics to enable automated quality monitoring using an industrial camera in the textile industry. Here, an autoencoder is used, which can be defined as an artificial neural network. Validation and testing of the algorithm are performed using various defective example fabrics from a rotary printing process. This is followed by assessment and evaluation using predefined assessment metrics.

State of the art

Historically in manufacturing, the majority of anomaly detection tasks are performed by humans, which suffers from disadvantages such as human fatigue and operational costs. Hence, the primary objective of automated anomaly detection is to minimize human intervention, enhance productivity, and improve product quality.

Based on the needs, many automated optical quality control systems for textiles have been developed [3-5]. Commercially available systems are typically rule-based and limited to simple, unpatterned textiles [6-9]. Some rule-based systems able to handle complex textiles (e.g., multicolored textiles or single-color jacquard fabrics) [7, 10] must be laboriously reconfigured for each item. Broadly speaking, existing anomaly detection systems in the market still exhibit limitations in generalization, usability, performance, computational cost, and interpretability. Combined with the complex operability of such systems, this results in an obstacle to the economical use of these systems in SMEs [1, 11].

Prior to the advent of deep learning, traditional anomaly detection algorithms such as statistical and structural methods exist [12], which usually require a great deal of priori knowledge, are computationally expensive, and often assume a specific data distribution, thus perform poorly on unseen data. Such image anomaly detection technique struggled to meet the standards of industrial manufacturing. In the present day, deep learning techniques have delivered commendable outcomes [2].

Current anomaly detection algorithms in the scientific field [13-15] often prioritize detection accuracy while overlooking the model's size and efficiency, which leads to high computational costs and restricts the application in enterprise production. Therefore, it is necessary to design light weight but efficient anomaly detection models.

Based on industrial requirements, an approach was designed using Autoencoder, which offers several advantages, including its ability to achieve effective training with a limited number of defect-free samples, its enhanced robustness and precision in comparison to general inspection methods, and its capacity to handle various, complex textile fabrics. By operating in a lower-dimensional feature space, Autoencoders can significantly reduce computational costs and memory requirements, making them suitable for real-time or large-scale anomaly detection applications. Furthermore, Autoencoders are robust as they are capable of handling noisy or incomplete data, which is often encountered in real-world scenarios.

Experimental

To first decide what machine learning methods for anomaly detection were most adequate for the problem, a Harvey Balls table was used to compare Supervised Anomaly detection, Semisupervised anomaly detection and, lastly, unsupervised anomaly detection. The comparison can be seen in table 1, where the completely dark circles account for one point, the half-painted circles for half point, and the white circles with the black contour for zero points. The result of the comparison of the required data complexity, robustness, accuracy, variability, and optimization effort, shows that the unsupervized anomaly detection is the best suited for the approach.

Table 2 Harvey Balls table to compare machine learning-based anomaly detection methods.

	Supervised anomaly detection	**Semisupervised anomaly detection**	**Unsupervised anomaly detection**
Required data complexity	○	◑	●
Robustness	●	●	○
Accuracy	●	◑	○
Variability	○	◑	●
Optimization effort	○	◑	●
Total	**1**	**2**	**3**

Within the realm of unsupervised learning, generative approaches, such as Autoencoders (AE) [16-18] and Generative Adversarial Networks (GAN) [19-21], have been used in the past for anomaly detection in many application areas such as manufacturing, medical imaging and cyber-security. Anomalies are detected by calculating the reconstruction error, i.e. the difference between the generated output with the input, and measuring its distance to a determined threshold, which is usually a factor of the standard deviation [16].

In this work, a Convolutional AE (CAE) architecture with 12 convolutional layers is proposed and tested to achieve an accuracy of over 90% for detecting anomalies on printed textiles. To choose the architecture, a Simple Auto Encoder (SAE) and two CAE [22], with 12 and 14 convolutional layers respectively, were tested against each other for accuracy. The SAE architecture was discarded because it was not able to properly reconstruct the input images after the training. Out of the 2 CAE architectures, the one with 12 convolutional layers was chosen because it trained faster and did not show difference in accuracy with respect to the architecture with 14 convolutional layers. A graphic representation of the chosen architecture can be seen in Figure 1.

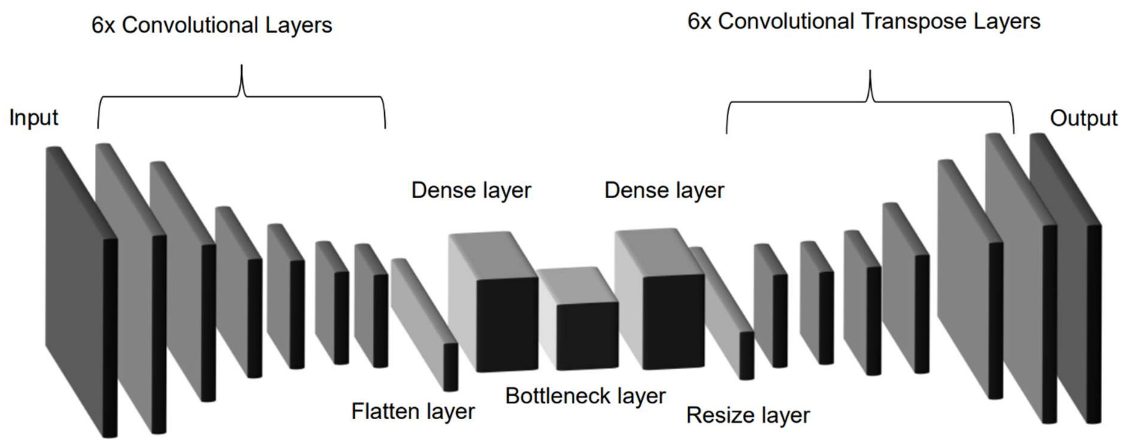


Figure 1: The chosen architecture with 12 convolutional layers, 6 in the encoder and 6 in the decoder, for the Convolutional Autoencoder.

Table 3 and Table 5 show in detail the properties of the encoder and the decoder respectively. While Table 4 shows the properties of the feature space.

Table 3 Properties of the convolutional layers of the encoder.

	Size	Kernel	Padding	MaxPool	Batch Normalisierung	LeakyRelu
Input	256x256x1	-	-	-	-	-
Conv1	256x256x2	(3,3)	Yes	-	Yes	Yes
Conv2	128x128x4	(3,3)	Yes	Yes	Yes	Yes
Conv3	64x64x6	(3,3)	Yes	Yes	Yes	Yes
Conv4	32x32x8	(2,2)	Yes	Yes	Yes	Yes

Conv5	16x16x16	(2,2)	Yes	Yes	Yes	Yes
Conv6	16x16x32	(2,2)	Yes	-	Yes	Yes

Table 4 Properties of the CAE's latent space.

	Size	**Activation function**
Flatten	8192	-
Dense layer	8192	Sigmoid
Bottleneck (Dense)	Variable numer of neurons	-
Dense layer	8192	Sigmoid
Resize	16x16x32	-

Table 5 Properties of the transpose convolutional layers of the decoder.

	Size	Kernel	Padding	Stride	Batch Normalisierung	LeakyRelu
ConvT1	256x256x1	-	-	-	-	-
ConvT2	256x256x2	(2,2)	Yes	-	-	Yes
ConvT3	128x128x4	(3,3)	Yes	(2,2)	-	Yes
ConvT4	64x64x6	(2,2)	Yes	(2,2)	-	Yes
ConvT5	32x32x8	(3,3)	Yes	(2,2)	-	Yes
ConvT6	16x16x16	(3,3)	Yes	(2,2)	-	Yes
Output	256x256x1	(2,2)	Yes	-	-	Sigmoid(x)

The training data was generated by taking grayscale pictures of five different patterned fabrics provided by E. Schellenberg Textildruck AG. These images had a resolution of 2048x1088 pixels and covered an area of 43.4 by 32.1 cm. To increase the proportion of the errors on the images and to augment the data to train the CAE, the images were segmented to windows of 512x512 pixels and were generated out of a sliding window of Δ=64 pixels, like shown in Figure 2. The 512x512 segments were then resized to 256x256 to fit the input layer of the CAE.

For each fabric, the segmented images were grouped into three datasets. The first dataset, used for training, only included images without printing errors. The second dataset, used for validation, was also limited to images without errors and had 40% of the images without errors. The third dataset solely included images with printing errors and was used as test dataset.

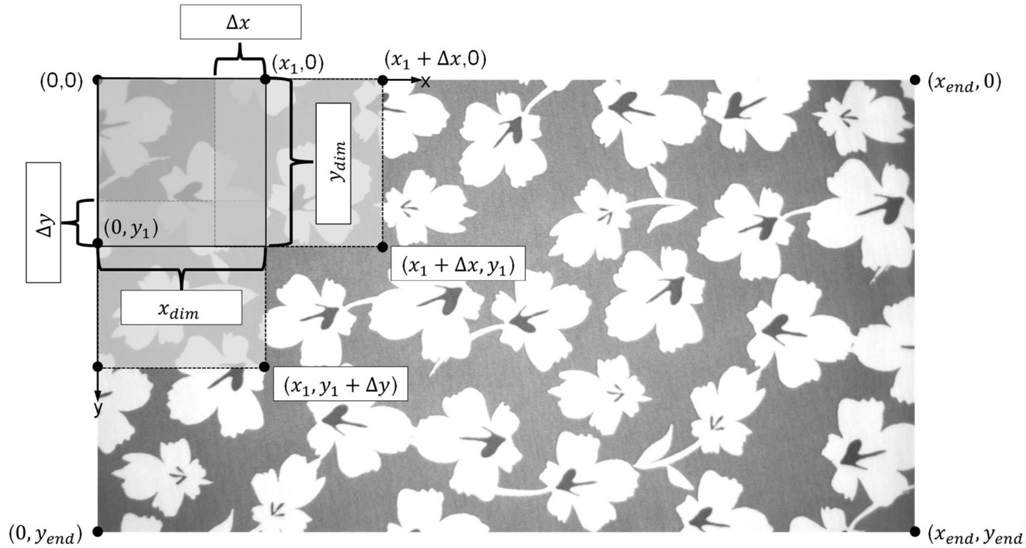


Figure 2 Picture of the third patterned fabric with a watermark of the window and its sliding stride.

In order to further improve the generic CAE architecture that can be applied to as many printed patterns as possible, a grid search for optimal hyperparameters (HP) of the CAE was carried out. In these experiments, 4 HP were optimized: learning rate (LR), the dimension of the CAE's bottleneck (D), the dropout, and the training epochs. Table 6 shows the value combinations for each parameter.

Table 6 Hyperparameter values.

Learning rate	0.001	0.0001	0.00001	-
Bottleneck's dimension	4000	900	600	300
Dropout	0	0.5	-	-
Epochs	50	100	-	-

To test the accuracy of each training iteration, a threshold that separates samples without printing errors from those with errors was defined by calculating the normal distribution of the reconstruction's Mean Squared Error (MSE) of images of the training dataset, and by setting the threshold to 3 times the standard deviation (σ), a value that was chosen experimentally when comparing it to thresholds of 1σ and 2σ. Hence, images that are reconstructed with an MSE larger than 3σ will be considered anomalies.

Results

The metrics chosen to measure the performance of the CAE are recall, precision, and accuracy, and all three confirmed that a generic CAE architecture is possible with the combination of HP LR=0.0001, D=4000, Dropout=0, Epochs=100. Table 7 shows what HP values performed better for each fabric.

With the selected HP combination, the lowest values of the metrics are recall=93.8%, precision=98.8%, and accuracy=93.6%, reaching the expectation of 90%.

Table 7 Ranking of the hyperparameter combinations, where 1 marks the parameter value that yielded the best metrics for a specific fabric.

Hyperparameter	Fabric 1	Fabric 2	Fabric 3	Fabric 4	Fabric 5	Sum	Rank
LR=0.001	0	0	0	0	0	0	3
LR=0.0001	1	0	1	0	1	3	1
LR=0.00001	0	1	0	1	0	2	2
D=4000	1	1	0	0	1	3	1
D=900	0	0	1	0	0	1	2
D=600	0	0	0	1	0	1	2
D=300	0	0	0	0	0	0	3
Dropout=0	1	1	0	1	0	3	1
Dropout= 0.5	0	0	1	0	1	2	2
Epochs=50	0	0	1	0	1	2	2
Epochs=100	1	1	0	1	0	3	1

Discussion

In this study, an approach was presented that leverages a CAE architecture for the task of anomaly detection in images of printed fabrics. The methodology demonstrates promising results in identifying anomalies within image datasets, but it is essential to acknowledge its limitations and room for improvement.

Our approach relies heavily on the availability of data for training the CAE. It necessitates a significant volume of pristine, anomaly-free images. This requirement underscores the importance of ensuring flawless production runs, particularly in the initial five meters of the process, to secure the foundational dataset necessary for training the model.

A crucial aspect of anomaly detection in images is the ability to not only identify anomalies but also to localize them within the image. The approach within this work does not explicitly provide information about the spatial location of anomalies within the image. This is a critical drawback, as it limits the utility of the model in applications where pinpointing the precise location of anomalies is vital, such as medical imaging or quality control in manufacturing. Researchers may consider integrating techniques like attention mechanisms or object detection methods to enhance anomaly localization capabilities. Other options to achieve localization are locating anomalies based on the joint probabilities of each of the Gaussian mixture components [23], or, for instance, improving the loss function by introducing a tight regularization [24], so that the loss function during training is more fluctuated, compared to the original CAE model that evaluates only reconstruction errors. Furthermore, a larger anomaly detection dataset with pixel-level annotations can be used to train a location-aware model. [2]

Summary

The text discusses challenges faced in contemporary rotary screen-printing machines that stem from airborne fluff settling on rollers, obstructing ink transfer to fabric and resulting in small, imperceptible inkless areas, particularly in intricate patterns. Manual quality control is impractical due to the substantial resources required, especially for high-quality textiles.

To address this issue, the work proposes a CAE with 12 convolutional layers, achieving an accuracy of over 90% for detecting anomalies in printed textiles. However, future work should focus on enhancing anomaly localization and reducing the model's dependency on large training datasets, aiming to make anomaly detection even more practical and efficient in textile manufacturing.

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