Anomaly Detection and Localization for Images of Running Paper Web in Paper Manufacturing

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Abstract: We introduce a new method based on convolutional autoencoders to detect and locate paper web anomalies that can cause web breaks during the paper production process. In this approach, we pre-process the images, captured by two high-speed cameras located at the opposite sides of the running paper web at a paper machine, in several steps to remove noises and separate the paper web areas from the background. After designing and training a convolutional autoencoder with non-anomalous samples, a novel anomaly score and map are defined to find and locate web irregularities based on an edge detector and a reconstruction error, defined by the combination of absolute error and Structural Similarity Index Measure between the reconstructed and the original images, in each test sample. By assessing the proposed approach on the images taken from a real paper machine, we discover that this method can detect paper defects properly and, therefore it has the potential to improve machine functionality and even to prevent certain types of web breaks, which reduces the machine downtime, paper losses, maintenance costs, and energy consumption, i.e., increases the performance and efficiency of paper machinery.

1 INTRODUCTION

Anomalies, also known as outliers, refer to the samples that differ significantly from the normal patterns of the majority of data (Yang et al., 2021). Anomaly detection involves the process of finding anomalous samples within a dataset, while anomaly localization refers to the techniques of specifying the defective area within an anomalous sample (Pang et al., 2021).

Anomaly detection has a wide range of applications across various industries, such as manufacturing and quality control (Rippel and Merhof, 2023), cybersecurity (Alabadi and Celik, 2020), and health monitoring (Fernando et al., 2021). In this work, we mainly focus on the visual application of anomaly detection in manufacturing products, specifically for identifying defects in images taken from running paper webs, which helps to predict and prevent web breaks that may happen when dirt or tear appears on the rapidly running paper web.

Generally, paper machines are designed for continuous operations and will only be shut down for predetermined maintenance periods that may take approximately three weeks annually. In this regard, unexpected stops, caused mainly by accidental web breaks, require equipment cleaning and additional maintenance periods, which not only increase machine downtime, paper losses, energy consumption,

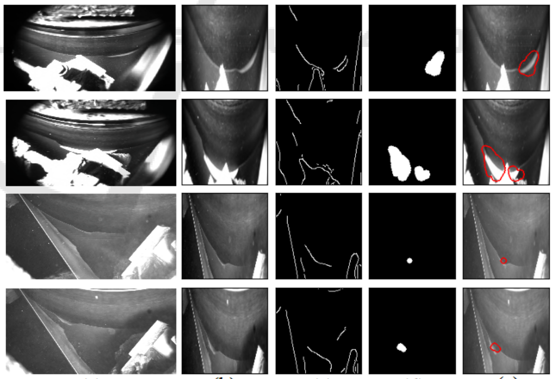

Figure 1: Detecting and locating anomalies in paper images taken from the front and back cameras installed in a paper machine. (a) Original image, (b) Cropped region of interest (RoI) including the paper web area, (c) prominent area detected by the edge detector, (d) Final anomaly map, (e) Anomalies highlighted on the top of the original RoI.

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and maintenance expenses but also reduce the product quality and efficiency of the machine (Dias et al., 2021). Due to these reasons, many companies try to monitor the running webs to detect and analyze the reasons for probable breaks in paper machines.

Many methods have been developed attempting to estimate paper web break sensitivity by using fuzzy logics (Ahola and Juuso, 2006), calculating paper break sensitivity (Bonissone and Goebel, 2002), or using classification approaches on the equipment's status (Sorsa et al., 1992). However, these algorithms only focus on detecting potential web break sensitivity indicators and cannot identify the root cause of the break. Moreover, none of them has tried to detect web anomalies from paper images as developing a high-performance visual detection method for this application is a challenging task due to some inherent complexities of the problem, such as rarity, unpredictability, unknownness, and variety of web irregularities, the existence of large noises, and the quality and availability of labeled data (Liu et al., 2023).

The main difficulty of visual anomaly detection in paper production lines is the varying image quality caused by light conditions, camera instability, environmental contaminants, and the high-speed nature of the process (Sorsa et al., 1992). Producing paper from pulps generates dust, debris, and contaminants (Haile et al., 2021) that affect the quality of images and create noises in the images by reflecting the light. Moreover, due to the narrow space and limited possibilities to attach the cameras to the desired positions around the paper machine, some machine instruments irrelevant to the paper web may appear in the images, which makes defect detection more challenging. Besides, various light conditions change the contrasts of images, and the high-speed nature of the process may also create some vibration and motion blur in the web area, resulting in poor quality of the available images, as is shown in Fig.1.

On the other hand, irregularities rarely occur during the normal paper production process, making it impractical to gather labeled anomalous samples (Pang et al., 2021) for training a supervised method (Rippel and Merhof, 2023) in reality. Moreover, the locations, sizes, and types of anomalies are unknown and unpredictable (Chandola et al., 2009), making the detection process even more difficult.

To deal with the abovementioned complexities, we present an efficient method based on an autoencoder (Tsai and Jen, 2021) with an edge-based attention mechanism to detect web anomalies from paper images. The model is trained in such a way that it can decode normal images properly from the encoded space while the anomalies cannot be recreated appropriately from the latent space, as a result of which the web defects will appear in the reconstruction error.

To detect and locate abnormalities, a new anomaly score and map are defined based on the combination of Structural Similarity Index Measure (SSIM) (Hassan and Bhagvati, 2012) and the absolute error (L1) between the reconstructed and original images. Moreover, in order to reduce the false detection alarms mainly resulting from the imperfect reconstruction of the moving machine parts and irregular illumination conditions inside the region of interest, we apply edge-based attention to focus on defects that occur in prominent areas, specifically on paper edges.

It is shown in section 3 that our approach is the first method that properly adapts a visual anomaly detection technique for detecting irregularities in paper images that can cause web breaks in paper machines. By assessing our method on the images taken from a real paper machine, section 4, we demonstrate that not only can this method detect subtle and large anomalies properly in a noisy imaging environment, but also it reduces the false detection rate which is very important in real applications as too high false detection rate practically drives the operators to deem the alarm system unreliable and to turn it off.

2 RELATED WORK

Although a few methods, developed mainly based on fuzzy logics (Ahola and Juuso, 2006) and calculating paper sensitivity (Bonissone and Goebel, 2002), attempt to detect web breaks in paper machines, there is still room for further improvement due to the inherent complexities of this problem. Since this paper is the first one in the literature that attempts to apply computer vision techniques to paper images to detect and locate defects that can lead to web breaks, we introduce state-of-the-art anomaly detection methods (Liu et al., 2023) in this section that might apply to this problem and discuss their advantages and limitations.

Many semi-supervised approaches (Pang et al., 2021), varying from autoencoders to self-supervised approaches and one-class classifiers that only utilize normal samples for training purposes, have been developed to deal with anomaly detection and localization in visual applications. Autoencoders (AEs) (Tsai and Jen, 2021), the most common and simplest methods, are designed to reconstruct an image from a latent space in such a way that only normal patterns will be reconstructed properly while the defective areas will be missed, as a result of which the difference between the original and reconstructed samples can be used to detect anomalies. Many variants of au-

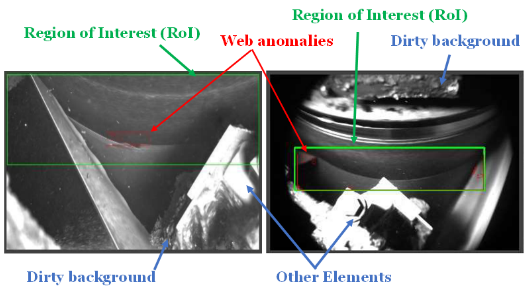

Figure 2: Sample images from paper machine demonstrating Region of Interest (RoI), anomalies, dirty background, and the existence of other elements. (left) Front camera, (right) Back camera.

toencoders with different types of topologies and loss functions (Bergmann et al., 2018; Bionda et al., 2022) are developed to detect visual anomalies.

Convolutional autoencoders (CAE) (Tsai and Jen, 2021) are the simplest forms of autoencoders that utilize several convolutional layers in their architecture. On the other hand, variational autoencoders (VAEs) (An and Cho, 2015) employ the distribution of latent space to increase the accuracy. In these methods, it is assumed that the latent space adheres to a specific probability distribution, commonly a Gaussian distribution. This distribution is used to create a regularization error alongside the reconstruction error to encourage the latent space to follow the Gaussian distribution, enhancing the model's efficiency. Although autoencoders are simple in structure and can detect large defects properly, they face problems in detecting small anomalies, specifically in the presence of large noises (Liu et al., 2023), which limits their usage in paper anomaly detection problems.

On the other hand, self-supervised approaches such as TPSAD (Dini and Rahtu, 2022) and CutPaste (Li et al., 2021) attempt to train a model with normal samples and simulated irregularities generated from a pre-defined proxy, which gives a better representation of the images for detecting irregularities. Most of these methods utilize a pre-trained model as the backbone structure and then fine-tune it based on the normal and simulated samples. Although these methods are able to detect small and large defects accurately, they are sensitive to noises (Dini and Rahtu, 2022) in such a way that even small noises in the images increase the false detection rate significantly. Moreover, simulating anomalies on the small area of the paper web is a big challenge in these methods as the web area represents only a small portion of the entire image compared to the background, Fig. 2.

One-class classifier methods such as (Dini and Rahtu, 2023) and PSVDD (Yi and Yoon, 2020) are other types of semi-supervised approaches that attempt to establish a decision boundary in the feature space of normal images and identify anomalous samples by recognizing those that fall outside this boundary. Some of these methods, like PSVDD (Yi and Yoon, 2020), divide the image into patches and attempt to find irregular patches, while others, such as (Dini and Rahtu, 2023), detect outliers based on the overall representation of images. Although these methods are effective at detecting subtle defects, they face scalability issues as the dimension of the related feature space increases (Pang et al., 2021) in addition to the fact that noises can affect their performance significantly. Moreover, analyzing patches separately for finding defects requires more computational resources in the training and testing phases, which limits the usage of these methods in real-time processes.

3 METHOD

3.1 Overview

The proposed anomaly detection approach consists of three main phases: pre-processing, training, and testing. The pre-processing phase is responsible for filtering, cropping, and resizing the train and test images in such a way that the final model is more robust against the noises and varying imaging conditions.

The convolutional autoencoder learns the normal patterns of the webs in the second phase since only normal images are used in the training process. In other words, in the case of web defects in the test samples, the model replaces them with normal patterns as it only has the information of normality.

In the testing phase and with the help of SSIM and L1 errors, post-processing filters, and an edge detector, an anomaly map is created for each test sample. The anomaly map indicates the exact locations of web defects in the test image, and the average value of the map expresses the level of abnormality of the image. It is good to mention that the edge detector plays a significant role in reducing false detection alarms as it filters out the large parts of the noise in the reconstruction error map. The model architecture of the proposed method is described in detail in Fig. 3.

3.2 Pre-Processing Procedures

Pre-processing step plays an important role in increasing the accuracy of the proposed method. Finding paper web anomalies from original images is a challenging task as they contain many irrelevant elements, and the web areas represent only a small portion of the entire images, Fig. 2. To address these complexities, the

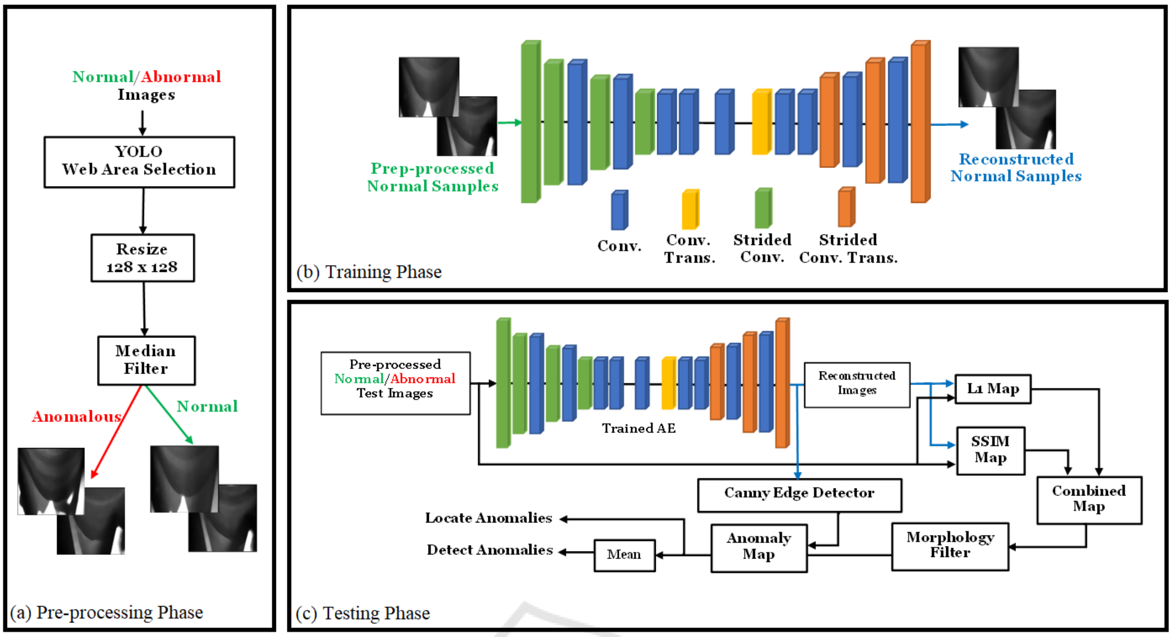

Figure 3: Overview and model architecture of the proposed method for anomaly detection and localization in paper images. (a) Pre-processing steps to specify web areas with YOLO (Adarsh et al., 2020) and filter noises with median filter, (b) Training the autoencoder model. (c) Testing phase to detect and locate defects with the help of edge detector.

YOLO (Adarsh et al., 2020) model is applied to the images to detect the web areas as the region of interest (RoI) to be utilized in the training phase. Specifically, the RoI in our application contains the paper web area and excludes large parts of the background. These regions of interest are resized to 128×128 to have the same size.

Due to the light reflection from dust and debris generated in the normal paper production process, white areas with different sizes appear in the images, which might be considered anomalies in the testing phase. To circumvent that, a median filter is utilized to filter small and medium noises. It is obvious from the images shown in Fig. 3(a) and more clearly in Fig. 5 that the web area and anomalies remain intact after filtering while the noises are filtered properly.

3.3 Model Architecture and Training

In the autoencoder-based methods, selecting a suitable model architecture is crucial and has a significant impact on the method's performance (Liu et al., 2023). An appropriate model should be able to capture semantic and detailed information to accurately recreate non-anomalous areas while avoiding defects.

In deep autoencoders with large bottlenecks, the model can reconstruct both normal and abnormal areas simultaneously, often leading to difficulties in detecting anomalies due to small reconstruction errors in the anomalous areas. Very shallow models may struggle to properly reconstruct even normal images, which can result in normal samples being falsely considered anomalies. Finding the right balance in the model architecture and bottleneck size is crucial to detect anomalies accurately without compromising reconstruction capabilities (Tsai and Jen, 2021).

To design a proper model, an encoder with 8 convolutional layers is utilized to encode images to a latent space, and then a decoder with 8 layers is used to reconstruct the image from the latent space as is shown in Fig. 3(b). We find out that using a combination of convolutional and convolutional transpose layers allows the decoder to give a better reconstruction image compared to using only convolutional transpose layers. The proposed model learns the normal patterns of web areas as it is trained with normal images while using the SSIM loss function as follows:

$$\mathcal{L}_{SSIM} = \sum_{i=1}^{N} (1 - SSIM(x_i, D(E(x_i)))) \quad (1)$$

where $x_i \in X_N$ is a training image and X_N is the set of normal samples used in the training phase. $E(x_i)$ represents the encoded space of the training sample x_i, while $D(E(x_i))$ represents the related reconstructed image. $SSIM(x_i, D(E(x_i)))$ calculates the structural similarity between the original and reconstructed images according to (Hassan and Bhagvati, 2012).

3.4 Web Anomalies Detection and Localization

To detect abnormal samples, it is essential to assign a numerical value, known as an anomaly score, to each data sample. By establishing an appropriate threshold on these scores, we can distinguish defective samples. Likewise, an anomaly map can be generated by attributing anomaly scores to individual pixels in an image, aiding in the identification of irregularities present in the corresponding abnormal samples.

To identify and locate web defects in the testing phase, each test sample is fetched into the trained model, and then the L1 and SSIM maps are created based on the difference between the original and reconstructed images. After setting a threshold on these maps and combining them together, a morphology filter is applied to remove the salty noises in the maps.

To reduce the false detection alarms generated from large noises, dirty backgrounds, and the existence of irrelevant elements, the edges of the paper web in each test image are found by the Canny edge detector (Canny, 1986), and then the overlaps between the filtered map and the web edges are used to create the final anomaly map. The average values of anomaly maps are thresholded to detect anomalous samples, and the related anomaly map represents the exact location of web anomalies. The testing phase is shown in Fig. 3(c) in detail.

4 EXPERIMENT

4.1 Dataset

To evaluate the performance of our method on a real-world application, we gather high-resolution grayscale images from two high-speed cameras installed on the front and back sides of a roller of a paper machine. The training dataset contains only normal samples for training the autoencoder, while the testing dataset contains a few images with anomalies in addition to the normal ones, as is shown in Tab. 1. Images from the front camera have 2040×1020 resolution while images from the back camera are 764×540.

Table 1: Number of samples in the test and train datasets for the front and back cameras installed in a paper machine.

Group	Train Dataset	Test Dataset	
	Normal	Normal	Anomaly
Front Cam.	5000	1318	19
Back Cam.	5970	1100	35

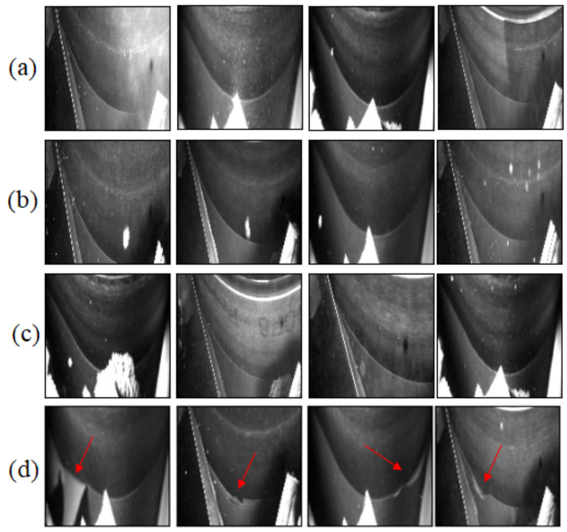

Figure 4: Samples variety and web defect detection challenges. (a) Normal images with various qualities and contrasts, (b) Normal samples with noises originating from light reflection from particles in the air, (c) Normal images containing various types of irrelevant elements and texts, (d) Anomalous images with various defect sizes and locations.

This dataset contains various images that represent the challenges of detecting paper web anomalies, mentioned in section 1, which makes it a suitable candidate to assess the performance and generalizability of the proposed method. Due to the harsh conditions at the paper production line, the images of this dataset have various qualities, Fig. 4(a), contain small and large noises, Fig. 4(b), and consist of multiple objects and uneven background that changes from image to image because the cylinder is rotating, Fig. 4(c). On the other hand, the web defects have various sizes, shapes, and contrasts that represent the unpredictability property of the anomalies properly, Fig. 4(d).

4.2 Metrics

To present our results, we calculated the accuracy, false positive rate (FPR), and false negative rate (FNR) for each camera dataset based on the best threshold and compared the results of our method with the recent anomaly detection approaches.

It is important to mention that accuracy alone might not be a proper metric to evaluate the performance of a defect detector as anomaly detection can be considered an imbalanced classification problem in which the number of anomalous samples is significantly less than the number of normal samples, resulting in the fact that a detector that detects all samples as normal ones will end up in high accuracy. However, it is still a useful metric as one can understand the difference between the method that cannot label the normal or anomalous samples properly and the one that is able to do so at first glance. On the other hand, the false positive and negative rates are proper metrics to describe the ability of the method to detect anomalous samples while avoiding false detections.

4.3 Implementation Details

To detect paper web anomalies, two separate autoencoders are trained with the images gathered from each camera. These models are optimized with the preprocessed normal samples, filtered with a median filter of size 9, and resized to 128×128. The Adam optimizer with a learning rate of 0.0002 and decay of 0.00001 is used for updating the model parameters for 200 epochs, considering SSIM as the loss function.

To create the anomaly map, the SSIM map with the kernel size of 5 (for the front camera) and 7 (for the back camera) are combined with the L1 map and then filtered with a 4×4 morphology filter to remove the salty noises. The overlap of the resulting map with the prominent edge areas, detected by the edge-based detector, defines the final anomaly map.

4.4 Results

We evaluated our approach on the above-mentioned real dataset and calculated the accuracy, false positive rate, and false negative rate for each camera dataset to demonstrate the ability of the proposed method while dealing with the paper web defect detection challenges. As there are no similar computer vision methods in the literature for detecting web anomalies from paper images to which we can compare the performance of our method, we also run a few image anomaly detection methods on the dataset, such as a self-supervised method TPSAD (Dini and Rahtu, 2022), a patch-wise one-class classifier method (Dini and Rahtu, 2023), a variational autoencoder (An and Cho, 2015), and convolutional encoders with various loss functions (Bergmann et al., 2018; Tsai and Jen, 2021) and compare the results in Tab. 2.

In general, our expectation is that our method accurately detects defects without mistakenly identifying anomalies in normal images or missing anomalous samples, resulting in high accuracy and low false positive and negative rates. It is important to mention that reducing the false positive rate is an important issue in our application as the cameras installed in paper machines are high-speed cameras, operating around 50-100 FPS, that take a lot of images from the high-speed running paper web during the production process. In this regard, even a small reduction in false positive rate can improve the usability of the defect alarming system considerably, considering the huge number of images taken daily in real applications.

In terms of accuracy, it can be deducted from Tab. 2 that our approach has better accuracy than other methods, implying the fact that most normal samples are labeled properly, as well as some of the abnormal samples, with different shapes, contrasts, and sizes of anomalies. By comparing the accuracy of different methods in Tab. 2, one can conclude that TPSAD and patch-wise methods are not able to label normal samples properly, considering the fact that their accuracies are low. By analyzing the results, we find out that many normal samples are detected as abnormal ones mistakenly by the Patch-wise OCC and TPSAD methods due to the existence of noises in the images.

Moreover, by comparing the false positive rates in Tab. 2, we find out that our approach has the smallest FPR amongst all the compared methods. This can be considered as one of the prominent achievements in our work, as it indicates that our method can properly reduce the false alarms that might be caused by the noisy environment in our application.

By comparing the false negative rates of the proposed method with other approaches, we discover that VAE (An and Cho, 2015), CAE (Tsai and Jen, 2021), and the one-class classifier (Dini and Rahtu, 2023)

Table 2: Comparison of our approach with the recent methods, CAE (SSIM) (Bergmann et al., 2018), CAE(SSIM, L1) (Tsai and Jen, 2021), VAE (An and Cho, 2015), TPSAD (Dini and Rahtu, 2022), and Patch-wise One-Class Classifer (Dini and Rahtu, 2023) results in paper web defect detection using accuracy, FPR, and FNR metrics.

Group	Back Camera			Front Camera		
	Acc (%)	FPR (%)	FNR (%)	Acc (%)	FPR (%)	FNR (%)
CAE(SSIM) (Bergmann et al., 2018)	98.23	0.45	40.0	98.65	0.38	68.43
CAE(SSIM,L1) (Tsai and Jen, 2021)	98.67	0.81	17.15	98.57	0.75	47.37
VAE (An and Cho, 2015)	96.03	3.7	11.5	95.43	4.09	36.85
TPSAD (Dini and Rahtu, 2022)	70.83	28.72	42.85	69.25	30.27	63.15
Patch OCC (Dini and Rahtu, 2023)	56.2	45	5.7	60.80	39.22	**36.84**
Ours	**99.91**	**0.09**	**2.85**	**99.1**	**0.22**	47.38

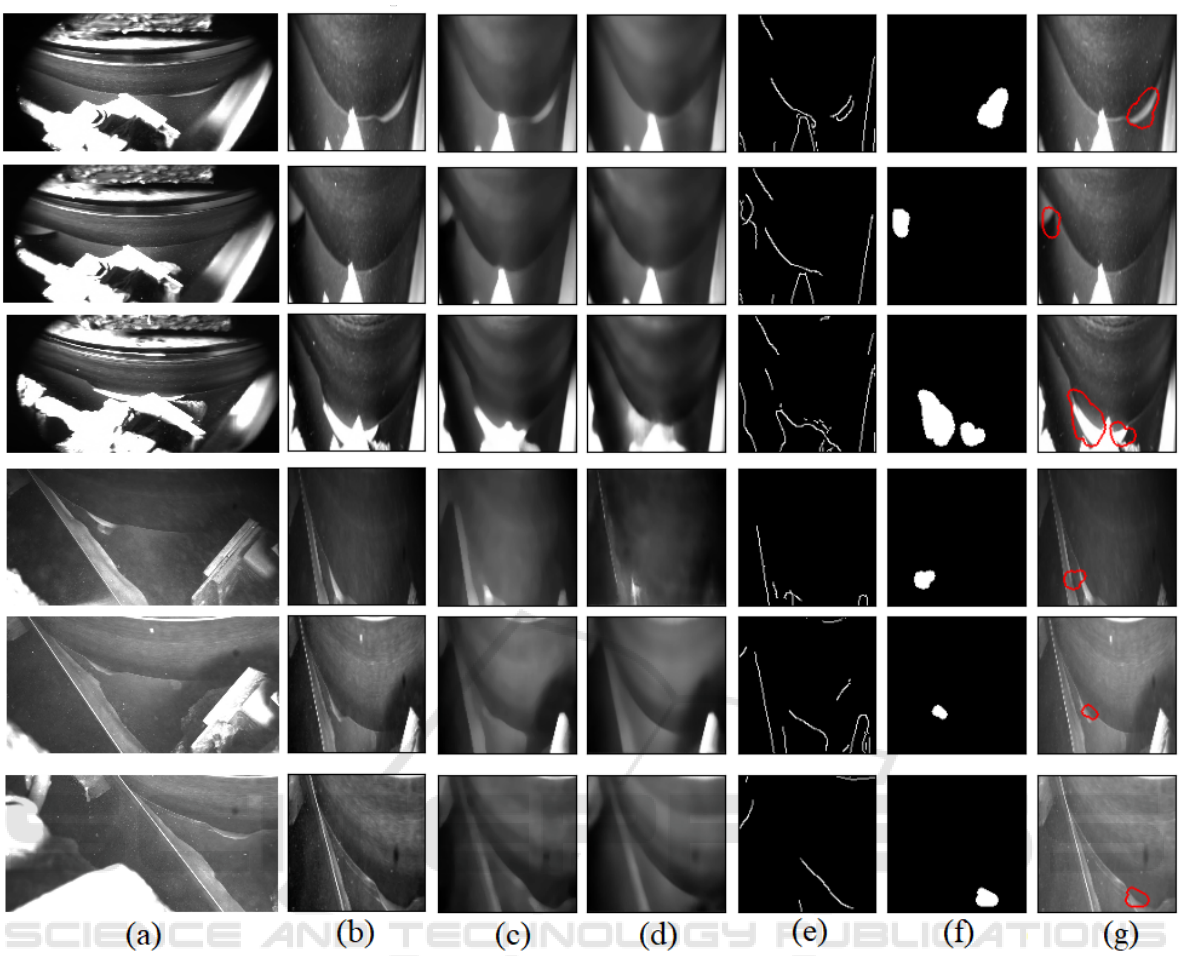

Figure 5: Visualization of paper web anomaly detection and localization using the proposed method, first three rows are images from the back camera, and the last three rows are from the front camera. (a) Original camera frames, (b) Cropped RoI resized to 128×128, (c) Filtered by median filter, (d) Reconstructed images by the trained autoencoder, (e) Prominent areas detected by the edge attention technique, (f) Final anomaly map, (g) Located anomalies highlighted on top of the original RoI.

have lower false negative rate than our method in one of the two camera datasets, meaning that a smaller amount of defects are missed. However, they have significantly larger false detection rates which limits their usage in real applications. In other words, since these methods are sensitive to noise, quality of images, and changing contrast in the images, they do not show proper results in our application. Some of the detected defects are shown in Fig. 5 indicating the fact that our approach not only can deal with the unknownness, unpredictability, and rarity complexities of the anomalies but also locates the web defects properly with the help of the anomaly map.

By comparing the first three and last rows of Tab. 2, the benefits of integrating an edge detector within our method become more evident. This integration leads to a significant reduction in the false positive rate by effectively filtering out the defects that occur only in the prominent areas of the image.

It is also good to mention that our approach has proper generalizability, according to which it can be used in different paper machines with minimum effort. Since most of the paper production lines resemble each other in terms of process, structure, and devices, one can use our three-step approach to preprocess images, fine-tune the autoencoder, and detect paper defects by defining a proper anomaly map with the help of an edge detector although there might be minor differences in the position of cameras, viewing angles, and contrast from one machine to another one.

5 CONCLUSION

The proposed method, developed based on the convolutional autoencoders for detecting and locating web defects on the prominent areas of paper images detected by an edge detector, is the first technique in the literature that aims to utilize visual anomaly detection approaches in paper applications. Through the evaluation of our method on the paper images, we demonstrate that the proposed method not only has the superior ability to detect and locate different types of unknown anomalies but also can properly deal with the inherent complexities of the paper web defect detection problem such as the effects of large and small noises, as well as the presence of irrelevant objects and dirty backgrounds. Showing high accuracy, low false detection rate and low false negative rate makes our approach a suitable candidate for detecting paper irregularities in real-world applications.

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