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Review of Fabric Defect Detection using Machine Learning Algorithms

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Abstract
This research article focuses on the critical task of fabric defect detection in textile corporations. Fabric defects adversely affect quality and profitability, making their identification crucial. Traditional human visual inspection is inefficient and impractical for mass production due to low detection rates and labor-intensive processes. To overcome these challenges, we propose an alternative approach to enhance efficiency and accuracy in fabric defect detection, ensuring the financial success of textile manufacturers in the face of increasing production complexity.

Keywords: fabric defect detection, object detection, convolutional neural network, prediction

Introduction

The detection of fabric defects is a crucial step in the quality control process for textile corporations. Fabric defects negatively impact the fabric's overall quality, appearance, and properties, leading to a decline in manufacturers' profits. In some cases, these defects can result in significant losses of up to 45–60% as prices are reduced to compensate for the compromised fabric quality and impact the consumption per garment [1]. Therefore, identifying and addressing fabric defects is of utmost importance to ensure the financial success of textile manufacturers. Traditionally, fabric inspection is accomplished by human visual checking however, the human detection rate only reaches up to 12 meters per minute [2], and is a monotonous job with high repetition, wasteful use of human resources, higher labor costs, exhaustion, tediousness, negligence, inaccuracy, time-consuming and with low efficiency, making it unsuitable for use in mass production. While human detection of fabric defects may be straightforward, the increasing complexity of cloth production lines and fabric outputs poses challenges for workers in accurately pinpointing the location of defects.

Furthermore, recognition errors brought on by worker weariness and the challenge of finding minor, subtle faults make the results of manual inspections untrustworthy. Human fabric flaw identification is therefore no longer appropriate for contemporary textile manufacturing. In line with the trends toward automation and digitization, the sector will inevitably go in the direction of computer vision-based systems to replace manual detection. There is still no widely used automated fabric inspection machine despite more than three decades of active development in this area. The key challenge is that current methods are not flexible enough to handle different kinds of faults. Therefore, improving the detecting algorithms is essential to creating a successful automatic fabric inspection device. Defect detection is done during production while using automated inspection. In real-time inspection, these systems detect the defect and are able to stop the production process just when the defect has occurred [3].

Techniques in artificial intelligence have the potential to revolutionize decision-making across a range of industries by providing extremely effective and affordable solutions. Consequently, there is a rising need for sophisticated detection technologies that may be incorporated into current fabric inspection equipment. Fabrics are also becoming more intricate and textured in a wider variety as the textile industry develops. The development of weaving technology has increased the prevalence of subtle and microscopic flaws, making the detecting process more difficult. Therefore, it is crucial to do research and create a solid model for identifying fabric flaws that is very accurate and effective.

Literature Survey

In this section, we delve into an extensive examination of the research and theories concerning fabric defect detection and its associated technologies. Through a thorough study, we seek to acquire a profound understanding of the subject, encompassing various methodologies and approaches utilized in this domain. However, it is imperative to acknowledge the dynamic nature of technology and research, wherein newer advancements and innovative solutions continuously emerge, leading to a growing array of competing alternatives. Consequently, while our proposed solution represents a well-informed approach based on existing knowledge and research, its long-term viability may be influenced by the ever-evolving landscape of fabric defect detection. To remain effective, we must remain adaptable and open to future developments, ensuring our solution remains relevant and robust in the face of emerging challenges and advancements in this field.

The authors Chen et al. [4] discuss a unique approach to fabric defect detection called Faster GG R-CNN. This method overcomes difficulties associated with background texture by combining Gabor kernels. The model achieves exceptional accuracy by utilizing a two-stage training strategy with the Genetic Algorithm and back-propagation. It also greatly outperforms the conventional Faster R-CNN in terms of performance. This method has a mean average precision of 94.57%, compared to Faster R-CNN's 78.98%, and it shows tremendous promise for improving the textile industry's fabric flaw detection and quality control.

The paper by Zhang et al. [5] proposes a robust automatic fabric defect detection method using a deep convolutional neural network (CNN) which is considered to be highly effective in various computer vision tasks, such as image classification, object detection, and segmentation. This method includes three essential steps: breaking up the image of the fabric into local patches and labeling them; applying transfer learning to an already-trained deep CNN using the labeled patches; and detecting defects by sliding the trained model over the entire image during the inspection phase to find out the type of defect and where it is located. The method is tested on a variety of different fabric databases, and it demonstrates greater performance when compared to methods that are considered to be state-of-the-art in terms of both quality and robustness. This approach presents a promising solution for rapid and accurate fabric defect detection in the textile production process.

Ngan et al. [6] have studied the wavelet transform for automated defect detection on patterned fabric. Fabric defect detection utilized three distinct methods: Direct thresholding (DT) using wavelet detailed sub-images, the golden image subtraction method (GIS), and the wavelet pre-processed golden image subtraction (WGIS) method.

From the three methods, WGIS is specifically designed to address repetitive patterned textures and achieved the most favorable outcomes. In evaluating patterned Jacquard fabric, the overall detection success rate reached an impressive 96.7%. In this assessment, the accuracy and efficacy of the method were evaluated by comparing 30 defect-free patterned images with 30 defective patterned images.

The approach used by Jin and Niu [7] enhances the YOLOv5 object detection algorithm with a teacher-student architecture to handle limited fabric defect images. The deep teacher network accurately identifies defects, while the shallow student network achieves real-time detection with minimal performance degradation through information distillation. In addition to this, multitask learning is implemented in order to identify both general and particular flaws at the same time. The performance of the suggested approach for pattern recognition is greatly improved when a focal loss function and central constraints are included in the algorithm. Evaluations carried out on publicly available databases have shown that it is superior to other methods, drawing attention to its exceptional flaw identification capacity in photographic images of textiles. This method shows great potential for revolutionizing fabric defect detection in the textile industry.

Jiang et al. [8] used the method based on the Dense Net, SSD algorithm to enhance fabric quality control in the production process. Traditional methods struggle with complex and variable defect shapes, so the proposed approach aims to address these challenges. In this approach, the Dense Net network is employed as the backbone in the SSD algorithm, replacing the traditional VGG16. By doing so, feature map transfer is improved, gradient disappearance is mitigated, and network parameters are reduced. These modifications result in enhanced detection accuracy and real-time performance compared to SSD. During testing, the method achieves an impressive 78.6mAP accuracy and a detection speed of 61FPS. Altogether, this adaptive fabric defect detection approach showcases promising results and holds great potential for fabric quality control applications.

A learning-based framework for the automatic detection of fabric defects has been proposed by Zhou et al. [1]. The framework first crops the original image into a fixed-size square slider and then enhances each cropped image using improved histogram equalization. Following this step, the Inception-V1 model is utilized to make a prognostic regarding the presence of flaws in the immediate vicinity, and ultimately, the LeNet-5 model is utilized to identify the specific sort of flaw present in the fabric. The structure is made up of two stages: the first is the local defect prediction, and the second is the global defect recognition. Experiments conducted on the dataset provided conclusive evidence that the framework possesses superior performance in the detection of fabric defects.

The improved YOLOv4 algorithm used by Gao et al. [9] is a deep learning algorithm that uses a new SPP structure with SoftPool instead of MaxPool to improve the accuracy of fabric defect detection. The approach additionally makes use of contrast-limited adaptive histogram equalization in order to improve image quality. As a result, the mAP (mean average precision) is improved by 6%, although the FPS (frames per second) is only reduced by 2. The YOLOv4 algorithm has been enhanced to the point that it can rapidly and correctly locate the location of faults, and it can be used in other industries that detect problems as well.

In their paper, Wang et al. [11] describe a strategy to improve accuracy and time efficiency in the textile manufacturing business that is based on a multi-scale convolutional neural network (MSCNN). In order to provide a more accurate representation of extremely minute flaws in the fabric, the MSCNN builds feature maps at many scales. In addition, in order to cut down on the amount of time spent computing, a method for locating defects that is both speedier and uses information about their sizes that are already known has been developed. Experimental results show that the MSCNN achieves over 92% accuracy for each defect and a frame rate of more than 29 FPS. The proposed MSCNN accurately detects tiny-scale fabric defects and achieves a detection speed of 30 m/min, meeting industrial requirements effectively.

Detecting defects in the presence of sophisticated background texture remains a challenge. To address this, Chen et al. [15] proposed an improved Faster R-CNN model, called Faster GG R-CNN, by incorporating Gabor kernels from frequency analysis. When it comes to training the new model, they make use of a two-stage training strategy that is based on the Genetic Algorithm and back-propagation. Extensive trials support the efficacy of the suggested method by demonstrating that the Faster GG R-CNN exceeds the regular Faster R-CNN in accuracy. This is demonstrated by the fact that the Faster GG R-CNN achieves a mean average precision of 94.57%, whilst the standard method only achieves 78.98%.

An artificial intelligence-based automated fabric defect detection technique is presented by Sashikumar et al. [11]. This approach makes use of pre-trained deep neural network models in order to categorize fabric faults. Before training the Deep Convolutional Neural Network (DCNN) and the pre-trained network, AlexNet, the fabric photos go through a process called pre-processing, which involves the use of traditional image processing techniques to enhance the features of the images. During simulations, this method reaches a maximum accuracy of classification that is equal to 92.60%.

METHODOLOGIES

A. *R-CNN*

It is suggested to use neural networks and the Gabor filter to detect fabric defects. Faster R-CNN is chosen as the neural network structure because it performed well in automatic target identification for several public data sets (Sun et al., 2019, Mudumbi et al., 2019, Xu et al., 2019). Additionally, the Faster R-CNN is enhanced by including a Gabor filter as the first convolutional layer in order to get rid of the background texture. They also used an integrated Genetic Algorithm (GA) to optimize Gabor parameters for fabric defect detection. The accuracy of our detection model is evaluated using the Average Precision (AP) value, which served as the fitness function for GA. To address fabric background interference, they incorporated an optimized Gabor filter into the Faster R-CNN detection model. GA is then utilized to determine the most effective Gabor filter parameters. Unlike previous approaches that relied on empirical functions or middle indices, they employed the final accuracy index of the detection model as the fitness function for GA, enabling them to select the optimal Gabor filter parameters (Roberge et al., 2018, Reddy et al., 2020, Sun).

B. WGIS

The Wavelet Transform (WT) is utilized in the creation of an automated visual inspection approach for the purpose of fault detection on patterned fabric. The method incorporates two approaches: Direct Thresholding (DT) based on WT detailed sub-images and the Golden Image Subtraction method (GIS). The GIS method proved to be efficient and fast, effectively segmenting out defective regions on patterned fabric. Furthermore, a new method called Wavelet Preprocessed Golden Image Subtraction (WGIS) is introduced. It involves decomposing the original image using wavelet transform, creating a reference or" golden" image representing the defect-free version, and then subtracting the transformed original image from the golden image.

This process highlights the differences, making it easier to detect the defect on patterned fabric or repetitive patterned textures. When evaluated on a dataset consisting of 30 defect-free photos and 30 defective-patterned photographs of a typical type of patterned Jacquard fabric, the WGIS approach revealed a high identification success rate. The dataset contained both images with and without defects.

C. CNN

Defect detection algorithms are assessed based on three criteria: the detection rate, indicating the sensitivity of the model, the false alarm rate, measuring its robustness, and the model efficiency, determining its suitability for industrial applications. Drawing from recent developments in deep learning, this innovative approach utilizes a sparse CNN integrated with an Inception module to predict visual defects. The main aim is to identify an optimal sparse structure within the CNN, which is then complemented and approximated by dense and readily available components. This enhances the overall efficiency and effectiveness of the detection model.

The collection includes 2000 photos with flaws and 3000 photographs without flaws, the majority of which are from the Tianchi competition. Furthermore, the photos with flaws are divided into three categories. All photos have a resolution of 2560 x 1920. They purposefully created some fake creases on the fabric surface to improve data generalization. In order to train the local defect prediction model, they crop the original image using a frame that is 224 pixels by 224 pixels. The area of the image that contains the defect is considered a positive sample, while the portion of the image that does not contain the defect is considered a negative sample. The negative sample collection contains not only photos that are considered to be normal but also unaffected portions of images that have faults. Using this method, they obtain a training dataset of approximately 200,000 photos. The majority of the photographs in the dataset were obtained from the Tianchi competition. The dataset contains a total of 5000 images, 2000 of which are flawed and 3000 of which are flawless. In addition to this, the photos that have flaws are separated into three distinct categories. All of the photographs have the same dimensions, which are 2560 by 1920.

Purposefully some false creases were created on the surface of the fabric so that the results would be more representative of the population as a whole. To train the local defect prediction model, they employ a cropping technique on the original image, generating frames of 224 pixels by 224 pixels. The region of the image containing the defect is treated as a positive sample, while the portion without the defect is treated as a negative sample. The negative sample dataset is comprised not only of photos that are considered to be normal but also of parts of images that appear to have flaws that are completely innocent. By utilizing this strategy, they are able to obtain a training dataset that contains approximately 200,000 photos.

The performance of defect detection algorithms is evaluated in this study utilizing the aforementioned four different evaluation indicators. For the evaluation, the metrics utilized include detection rates (DR), false alarm rates (FR), the area under the curve (AUC), and detection success rates (DACC).

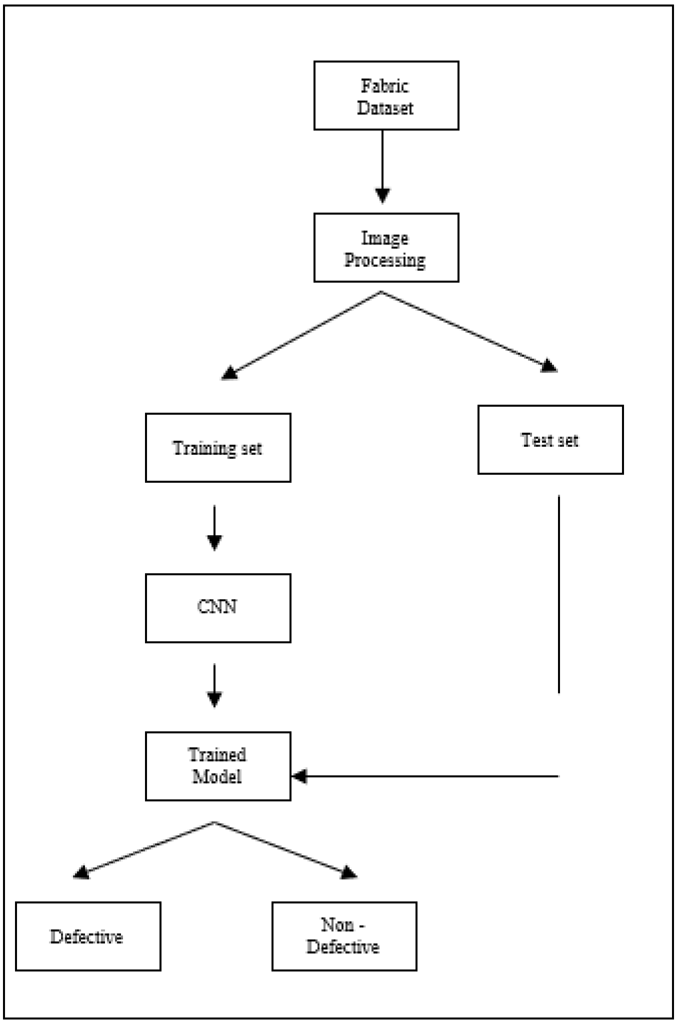

Fig. 1. Fabric Defect Detection Flowchart

D. YOLOv5

In this study, a deep learning approach is used to automate the detection of fabric defects, which results in an improvement to the YOLOv5 object detection technique. The images for fabric defects are scarce so to solve the issue, a teacher-student architecture is utilized, with a proficient deep teacher network accurately recognizing fabric defects. The evaluation is conducted on publicly available databases comprising 3,331 labeled images, specifying rectangular locations of defects. Among the images, 2,163 are categorized as normal, while 1,168 contain defects encompassing 22 different types such as knots, jumps, puncture holes, stains, and lacking warp. The dataset exhibits an imbalanced distribution, with a significantly higher number of normal images compared to defective ones.

The defect categories are combined following a standardized experimental protocol, resulting in distinct groups like puncture holes, brushed holes, rubbing holes, knots, lacking warps, stains, and others. During the experimental phase, 70% of the database is allocated for training the model, while the remaining 30% is reserved as the test set. The main objective of the defect detection algorithm is two-fold: firstly, to distinguish between normal and defective fabric images, and secondly, to identify and categorize specific fabric defects. Consequently, the evaluation utilizes the area under the ROC curve (AUC) to measure the algorithm's capability to differentiate between normal and defective images. Additionally, the mean average precision (mAP) is employed to gauge the algorithm's effectiveness in recognizing and localizing specific fabric defects.

E. YOLO v4

The mAP of YOLOv4 with three SPP structures is lower than that of its counterpart with one SPP. The enhanced YOLO v4 utilizes an improved SPP (Spatial Pyramid Pooling) based on SoftMax. Additionally, three additional convolutions have been incorporated into the upper and middle parts of the enhanced SPP to further enhance the training effectiveness that boosts calculate performance and reduces running memory. The dataset utilized in this research is a combination of samples from Aliyun FD10500, Kaggle, and real photographs. It consists of a group of similar defects, including splicing, thick place, thin place, needle line, coarse end, and coarse pick, all characterized by elongated, slender shapes along the warp and weft direction. Due to their resemblances, these faults are collectively referred to as LINE defects. FLOATS refers to floats and ladder problems that are extremely damaging and nearly impossible to repair or eliminate. Because holes, knots, naps, and snags have small regions, they are difficult to detect.

These flaws are referred to as HOLE flaws. Furthermore, the faults of color leakage, dye masking, and oil stain are identical and are referred to together as STAINs. This study assesses three performance metrics, namely mAP, precision, and recall. The study includes a comparative analysis of five algorithms: YOLOv4 with enhanced SPP and CLAHE, YOLOv4 with CLAHE, the original YOLOv4, Faster RCNN, and SSD. The findings demonstrate significant enhancements in the modified YOLOv4 proposed in this research, in comparison to the original YOLOv4. The enhanced YOLOv4 considerably improves recall and precision for the minor fabric defect HOLE. The network model is appropriate for detecting fabric defects. To begin, they separated the anchor based on the features of the faults and averaged the results to make the anchor more suitable for the application. the image underwent CLAHE processing to eliminate unnecessary color information and enhance the contrasts within the image. Ultimately, the utilization of soft pooling instead of maximum pooling has led to a noteworthy improvement in the SPP structure. Consequently, the performance of the YOLO model has been significantly increased.

F. MSCNN

In this, MSCNN demonstrates the capability to extract diverse pixels from defect feature maps, leading to enhanced visualization of small-scale fabric flaws. Moreover, this study presents an expedited defect localization method that employs K-means clustering analysis to acquire defect bounding boxes, utilizing prior knowledge of defect sizes. This new method replaces the previous region generation approach, resulting in a notable improvement in defect detection speed. The MSCNN architecture is developed by combining feature fusion techniques with the VGG16 network. For experimentation, real-world fabric flaws commonly encountered in production settings are selected. To assess the fabric defect recognition algorithm, an automated fabric defect identification system is created, designed to gather fabric photographs for evaluation. These photographs serve as test samples to assess the effectiveness of the fabric defect recognition algorithm. There are two categories of fabrics in the fabric defect datasets which are linen fabric and patterned fabric and five types of defects, namely stain, end out, broken curse, double flat, and hole. During their experiments, two evaluation criteria were utilized: mean average precision (MAP) and frames per second (FPS).

The study conducts a comparative analysis of detection performance using several deep learning algorithms, including fast R-CNN, faster R-CNN, Yolo, Yolov3, and SSD. Several object detection models, including fast R-CNN, faster R-CNN, and SSD, employ the VGG16 network as the underlying architecture. On the other hand, Yolo is built upon DarkNet17, which exhibits a comparable depth of convolutional layers to the MSCNN model. On the other hand, Yolov3 is based on DarkNet53, incorporating 53 layers. It is worth noting that fast R-CNN and faster R-CNN employ a region proposal network (RPN) for defect localization. The bounding boxes created at random, which have no prior knowledge of the magnitude of the problems, are used by the SSD, Yolo, and Yolov3 to find the flaws. By building a multi-scale neural network, the MSCNN has a greater detection accuracy than both fast R-CNN and faster R-CNN when the depth of the network is the same.

G. DCNN

Pretrained deep neural network models are used in this AI-driven automated fabric defect identification algorithm to categorize possible fabric problems. Before training the networks, the fabric images are enhanced using a variety of traditional image processing techniques.

The Deep Convolutional Neural Network (DCNN) and the pre-trained network AlexNet were utilized in this study as models for the purposes of training and classifying various fabric defects. The training dataset is drawn from the huge collection of 540,000 photos in the publicly accessible MVTec Anoma ly Detection dataset, which includes five defect classes: color, cut, hole, metal contamination, and thread, as well as a non-defective class (labeled as "good"). This dataset is broken up into test and train sets, each of which has 180,000 and 360,000 photos. The gathered fabric dataset is first examined for damaged pixels before preprocessing, which includes methods like picture scaling, pixel normalization, and dimension reduction.

The DCNN model facilitates the characterization and analysis of fabric photographs, enabling the extraction of features from both imperfect and perfect textures. To aid in flaw detection and classification, the system is trained using datasets made up of both defective and non-defective fabric photos. An image is categorized as "good" if it is regarded to be clean; if not, it is categorized as "defective" and further classed into other types of defects, such as color, cut, hole, thread, or metal contamination. The DCNN's integrated image processing algorithms allow for accurate fabric flaw detection and categorization. The algorithm's effectiveness is tested on an existing textile dataset, showing admirable accuracy in the simulations that were run. This reliable detection and classification method may help human operators find errors in fabric manufacturing facilities.

III. Result Analysis

Author	Year	Method	Dataset	Defect Classes	Evaluation
Mengqi Chen [4]	2022	R-CNN	Defective Cloth Set	4	Precision
Rui Jin [7]	2021	YOLOv5	Xuelang Tianchi (3331)	22	ROC curve
Jiang Wang [1]	2021	LeNet-5 and Inception-V1	TILDA data set with defects (2000) and non-defect (3000) images	3	DR, false alarm rates FR, AUC, and detection success rates

Mingwang Gao [9]	2022	YOLOv4	Collected dataset (2687)	4	Precision and recall
Junliang Wang [10]	2020	MSCNN	Collected dataset (1000)	4	Precision and FPS and MAP
Henry Y.T. Ngan [6]	2005	Wavelet transform and GIS	Collected dataset: Defect (30) and non-Defect (30) images	6	Successes rate
Nihal Mathew Sashikumar [11]	2021	DCNN	MVTec Anomaly data set with defects (180000) and non-defects (360000) images	6	The sensitivity, specificity, PPV, NPV

Table. 1. Result Analysis of different algorithms

Conclusion

In conclusion, fabric defect detection using Convolutional Neural Networks (CNNs) has shown great promise in ensuring textile product quality. CNNs offer the advantage of automatically extracting intricate features from fabric images, making them adaptable to various manufacturing conditions. Real-time defect detection capabilities can improve production efficiency and minimize waste. Challenges such as data scarcity and overfitting need to be addressed, and future research can focus on data augmentation, transfer learning, and innovative architecture design. Despite these challenges, CNN-based fabric defect detection remains a powerful tool with the potential to revolutionize quality control in the textile industry, leading to enhanced product consistency and customer satisfaction. Collaborative efforts between researchers and industry professionals are crucial to advancing this technology further.

IV. Future Scope

We will offer a powerful machine-learning technique that looks for fabric defects. First, the fabric photos are improved using a powerful ResNet. Then, in order to anticipate whether there are flaws in the immediate area, we will use CNN, which is based on the Inception sparse network topology. The machine learning model is then used to vote and identify the flaw. Results from experiments show how excellent the suggested framework is.

The drawbacks of those deep learning-based methods over more conventional ones are their high computing cost and time requirement. Therefore, this study's current objective is to find ways to reduce detection time while keeping high accuracy. The majority of faults were simply categorized into three groups in this study, which included no-direction defects, warp-direction defects, and weft-direction defects. It is challenging to output the cause of the problems accurately because the suggested algorithm can only vaguely identify fabric defects. We will continue to research how to precisely identify the defect categorization utilized in the plant in the upcoming research as more data is gathered.

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