IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

IJARSCT
Impact Factor: 7.301

Volume 3, Issue 4, May 2023

A Survey on Fabric Identification and Defect Detection

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Abstract: *Due to the intricate geometries and wide diversity of fabric flaws, detecting them is a difficult task in the fabric industry. Numerous approaches have been put out to address this issue, but they all have very poor detection velocities and accuracy. As a traditional deep learning technique and end-to-end target identification algorithm, YOLOv4 has quickly developed and been used in numerous sectors with positive results. This study suggests a novel SPP structure that employs Soft-Pool rather than Max-Pool to detect fabric defects more accurately than the YOLOv5 method. The enhanced YOLOv5 method with three Soft-Pool has the advantage of processing the feature map efficiently, which significantly improves the detection accuracy and lessens the negative impacts of the SPP structure. The improved YOLOv5 can identify the location of defects accurately and quickly, and can also be applied in other defect detection industries.*

Keywords: Convolutional neural network, activation function, fabric defects, YOLOv5

I. INTRODUCTION

An essential step in the creation of fabrics in the textile industry is the inspection of fabric quality. More than 70 categories of fabric faults are established. The textile sector now relies significantly on manual visual inspection techniques, which leads to incorrect inspection results and higher manufacturing costs overall. Defective fabric will lose between 45% and 65% of its original cost. In order to increase the overall performance and reliability of fabric inspection and, at the same time, increase production and efficiency in the textile sector, it is required and appropriate to design an automatic visual inspection technique. Spectral, statistical, and model-based methods make up the three broad groups that best describe the currently available automatic fabric flaw identification techniques.

Comparing many fabric picture patches allows statistical algorithms to identify the distinctive statistical texture properties. Histogram character analysis, local contrast enhancement, and the fractal method are examples of existing statistical techniques. The primary drawback of statistical approaches is that the effectiveness of defect detection is strongly influenced by the size of the chosen sliding window and the discrimination threshold.

Additionally, they disregard the global information since they identify defective regions by comparing the differences between regions throughout the entire fabric image. By spectralizing the input images, spectral algorithms find the areas of surface defects. By converting the input images to the spectrum domain and calculating the energy of the filter responses, spectral methods identify the locations of surface defects.

Wavelet, Gabor, and Fourier transforms are a few of the spectrum techniques. When compared to statistical techniques, spectral techniques can effectively utilize global data on fabric image data. Model-based approaches use modelling and deconstructing techniques to address the issue of defect discovery.

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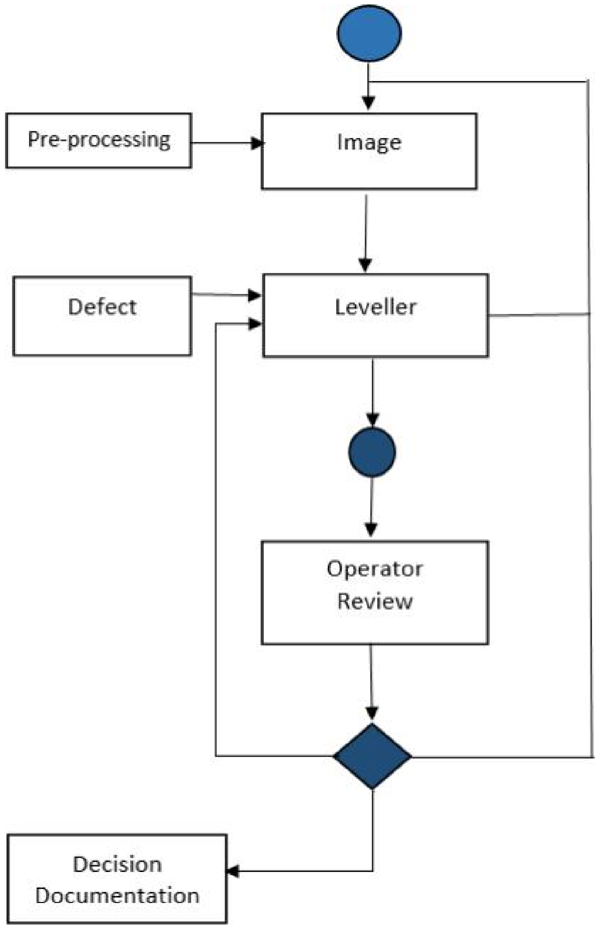
Operational flowchart: -



II. DATA GATHERING

For this work, three different datasets were used. In addition to two existing datasets (TILDA and stains dataset) and to have a more general dataset that could better represent the many different defect types observed in a production environment, a new dataset was created. The Fabric defect dataset was divided into two parts training and validation phases. TILDA (FD-TL) is a dataset developed by the group ‘‘Texture Analysis of the DFG’s’’. This dataset is divided into 8 different fabric types, each one containing seven defect classes, making a total of 3200 images.

III. MODELS:

YOLOv5

YOLO (You only look once) is an end-to-end neural network algorithm that has been continuously improved from YOLOv1 to YOLOv5. Numerous research papers have shown that YOLO has better speed and accuracy than the other algorithms. FPS (Frames Per Second) and precision are considered comprehensively. An improved algorithm based on YOLOv5 is proposed in this paper, where images from the dataset are enhanced in advance, and image processing is combined with deep learning to improve detection results. other algorithms. FPS (Frames Per Second) and precision are considered comprehensively. An improved algorithm based on YOLOv5 is proposed in this paper, where images from the dataset are enhanced in advance, and image processing is combined with deep learning to improve detection results. Boetal proposed the machine vision technique in which defects are detected by the Gabor filter, which is based on image processing, however, it has poor detection results for some types of defects. Wiener filter is used to classify defective images by converting RGB images into binary images to improve the detection effect. In addition, there are other methods to detect fabric defects. For example, a thermal-based defect classification method with K-nearest neighbour algorithm and dimensionality reduction to classify textile defects respectively. Image processing and thermal images are also used in defect detection. However, image processing and thermal image can only solve the classification problem. For these methods, the defects in the images are obvious, and defects can only be identified and cannot be located correctly. Most of the traditional image processing algorithms have the shortcomings that only simple background and large object images can be processed effectively. So the neural network based methods are been studied by some researchers. Then an activation layer embedded convolutional neural network was used to detect defects. Also combined image processing with deep learning and proposed a method in which image enhancement is implemented prior to using convolutional networks; accuracy was improved. Although the above algorithms are feasible, there are some disadvantages; some have slow recognition speeds and others have low recognition precision. Faster R-CNN is the most commonly used algorithm in fabric defect detection. Faster R-CNN, and its improvements, have been adopted by many researchers to increase the efficiency of detecting small targets. In general, the following are reasons for using Faster R-CNN. First, fabric defects have their own remarkable features compared to common defects. Among all kinds of fabric defects, there are some that account for a relatively large proportion in the images, such as WEFTS, WARPS, STAINS, FLOATS and CRACKYWEFTS, which is usually a very large spot, or the spot has the same width as the image. Other defects have small shapes (perhaps only a few pixels), such as NEPS, HOLE, SNAGS and KNOTS. Second, detection and recognition are relatively simple for large defects. However, detecting defects is very difficult for small targets, especially holes with only a few pixels, because the uneven number of positive and negative samples makes it difficult for a one-stage network to learn the features of small targets. Although this problem can also exist in a two-stage network, a large number of negative samples has a small impact on detection because the region proposal network (RPN) eliminates many negative samples. To solve the imbalance of the number of positive and negative samples in a one-stage network, We also proposed the focal loss method, which can reduce the weight of large sample losses and increases the weight of small samples in total loss. However, focal loss is not effective in practical applications, and evenly reduces MAP (mean average precision). Therefore, the precision of a two-stage network is generally higher than its one-stage network counterpart. However, a two-stage network represented by Faster R-CNN is generally as lower than the others. Therefore, the two-stage network is not adopted in this paper. As one of the typical first-order algorithms, YOLO has been improved over many generations. YOLO algorithms have developed rapidly, including YOLOv1 with various limiting accuracy problems, which was further improved in YOLOv2 and YOLOv3. Compared with YOLOv1, YOLOv2, YOLOv3 and YOLOv4, YOLOv5 has better performance and uses tricks to improve the accuracy. For example, mosaic data augmentation, MISH activation function, K-mean clustering algorithm, FPN-net, PAN-net, SPP-net and CSPdarknet53 are adopted as backbones. In addition, ordinary researchers can use a 1080Ti GPU to train a YOLOv45 model, which is beneficial to many scholars and is convenient for industry applications. Factories do not need to spend a large amount of time buying expensive hardware. Compared with the second- order algorithms, one-order algorithms represented by YOLO can meet the requirement for real-time detection. For the original YOLOv5, if 416 × 416 images are used as the input of the backbone, the generated sizes of the feature maps are (52,52,256), (26,26,512) and (13,13,1024) [33], and will revert to the original size in the final prediction. The bottom feature map of the backbone of the original YOLOv5 is (13,13), which passes the SPP structure after three convolutions. The original SPP structure of YOLOv5 is different from SPP-net, which has only three maximum pooling branches, and the results are converted to a one-dimensional vector, which then carries out full connecting classification. The SPP structure in the original YOLOv5 uses four branches. In the final output, the results of the four channels are superimposed, and the final number of channels is quadrupled. After three convolutions, the number of channels is reduced and then output to the FPN structure. The original SPP uses Maxpool that maxs pooling for each part, and solves the problem that the size of images inputted into CNN should be fixed. The SPP structure can enlarge the receptive field effectively, and the context features can be obtained more comprehensively by combining a pooling layer with different kernel sizes. The SPP structure has always been an excellent solution for classification and detection problems before the CNN appeared in. The pooling layer is the key component of the CNN network, because the parameters required by the network are greatly reduced, which can increase the receptive field of subsequent convolutions. Most frameworks adopt Max Pooling or AVG Pooling (average pooling). For example, the SPP structure adopts three max pooling filters with different kernel

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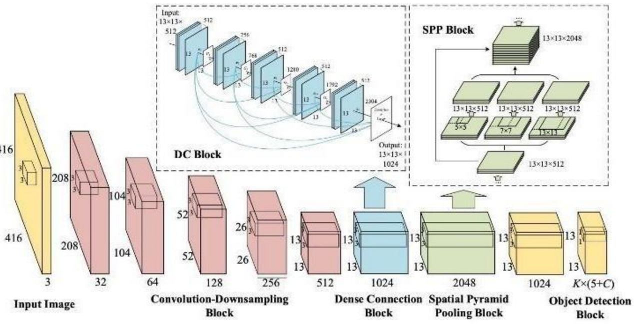
sizes, but max pooling will cause some problems when selecting the maximum value from a specific range (such as 3 × 3). Although max pooling can reduce the number of parameters, a large amount of information will be lost in the selection process. In addition, you do not know whether the information of the background or the target is lost because it only selects the point with the most obvious features as the representative of the neighborhood. If the background is similar to the target, it is easy to lose useful information. In the detection of fabric defects, as the defects are very similar to the background, the use of max pooling in SPP will affect the detection performance and has the risk of losing important features. In contrast, although AVG pooling takes into account all the features of the neighborhood and retains more background information, the target feature intensity of the region will be reduced, and the obvious features will be ignored after the average is taken.



CNN

Convolutional Neural Network is a specialized neural network designed for working with image datasets. It consists of convolutional layers where filters are applied to the input image. It improves the input's unnoticed features. The convolutional Neural Network analyses the paragraph it receives as input before categorizing them. It accepts input images and returns a class. The image is compared with each class and the probabilities of each class are returned. In CNN, the dot product of input image and kernel function is performed which in-turn decrease the size of the matrix resulting in loss of some features. Here padding is used to avoid feature loss/reduction. Convolutional, pooling, and fully-connected (FC) layers are the three basic types of layers that make up this neural network. With each additional layer, the CNN becomes more complex and obscures more of the image. There can be multiple convolutional layers and pooling layers, but fully- connected is the final layer.

FN:

AI anomalies can be handled with the proper categorization strategy. To eliminate false negatives in a targeted manner, the efficient method employs a cascade of models. While the second layer simply searches for negatives and any concealed positives in them, the first layer searches for both positive and negative classes. The following is a brief overview of the steps in the classification approach:

Initiate, transform and model these are three steps involved

Initiate:

Filter the principal classifier's output to just keep the negatives, or valid, typical observations. This process permits the reduction of some of the dataset's variation, which could result in simpler models and better learners. Create a fresh target using the old labels. Negatives suggest the original genuine negatives in this situation, while positives imply the original false negatives.

Since the original dataset is probably quite unbalanced, use appropriate sampling strategies to obtain balanced datasets. Due to the nature of the input dataset, which is a dataset produced by a classifier, the fraction of positive cases that the following method must learn (i.e., the first false negatives) will be quite small in comparison to the negatives (i.e. the original true negatives). To make sure the algorithm can learn successfully, this step is necessary.

Transform:

Transform the feature set nonlinearly. The examples from the original dataset that were most challenging to classify are those that were positives labelled in the previous stage. Given this situation, a non-linear transformation can be carried out to perhaps provide a better class separation in the ensuing procedure. Techniques for dimensional reduction can also be used to make the final model simpler. In order to avoid further complicating the flow, this enables the construction of simpler models.

To find the positives in the balanced dataset, use a secondary classifier (i.e. the original false negatives). To guarantee that models work as expected, regularly use model validation approaches. For classification and picture preprocessing, CNN is employed. The obtained photos are analyzed to reveal the fabric type and enable flaw detection. Then, taking into account all possibilities, YOLO is utilized to anticipate the detection of the defects on the cloth. In order to test different types of picture datasets, it is also used to train the model using a specific dataset. FN aids in providing the model's output and aids in doing appropriate analysis

IV. APPLICATIONS

- Fabric Industries
- Quality Control
- Fashion Industry
- Fabric error prevention

V. CONCLUSION AND FUTURE WORK

In order to identify textile fibers, this article presented a system that would use CNNs to extract features from the photos using the transfer learning approach. The findings lead us to the conclusion that real-world photos captured by a high-resolution camera can be used to identify textiles for garments.

Overall this system shows the potential of operator-assisted systems, which may be easier to implement, low-cost and better to tackle realistic scenarios. In this work, a new CNN-based fabric defect detection system, suited for a realistic scenario, was proposed. The CNN method provides a good feature detection, as it can be confirmed in Section V-C. This system has the possibility of being operator-assisted whom may confirm or reverse the system evaluation when a possible defect is detected. This increases the system accuracy by reducing the number of FP examples. Therefore, two FN reduction methods were studied. To obtain a reliable dataset that could represent most of the fabric defect types found in the literature, a new dataset was created. In total four different datasets were used to train and test the proposed methods.

As future work, it would be of interest to develop a larger dataset, with more real-world examples that would allow to train and implement a more complex defect detection system.

A larger dataset would allow the use of more complex models, such as GAN or Generalized Additive Model and Transformer networks. To improve the FN reduction functionality, more robust methods that can be executed during training, such as a custom loss function, could be tested. As a final objective, the developed system should be implemented in a real-world environment, to test and compare it to a traditional inspection system.

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DOI: 10.48175/IJARSCT-9833
ISSN 2581-9429 IJARSCT