IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

FABRIC DEFECT DETECTION

Prof. Neeta Ingale, Atika Ansari, Surabhi Yerunkar, Siddhi Thakur, Sadik Sayyed
Professor, Student, Student, Student, Student
Information Technology
Vasantdada Patil Prathishtan College of Engineering, Mumbai, India

Abstract: There are different applications of computer vision and digital image processing in various applied domains and automated production processes. Automatic defect detection is crucial in the textile industry as the quality and price of textile products rely on its efficiency and effectiveness. Fabric defect detection has been a challenging task, and manual human efforts were previously used to detect defects in the fabric production process. The major drawbacks of the manual fabric defect detection method are lack of concentration, human fatigue, and time consumption. Applications based on computer vision and digital image processing can handle the aforementioned limitations and drawbacks. Numerous computer vision-based applications have been proposed in research articles over the past two decades to overcome these limitations. The objective of this review article is to provide a comprehensive analysis of different computer vision-based techniques that are applied in the textile industry for fabric defect detection. The suggested study presents an extensive analysis of various techniques such as histogram-based methods, color-based methods, image segmentation-based methods, frequency domain operations, texture-based defect detection, sparse feature-based operations, image morphology operations, and recent advancements in deep learning. The performance evaluation criteria for automatic fabric defect detection are also presented and discussed. The disadvantages and limitations of the existing published study are thoroughly discussed, as are potential future research directions. This research study offers in-depth information on computer vision and digital image processing applications for detecting various types of fabric defects.

I. INTRODUCTION

Computer vision and image classification-based models are used in a wide range of applications, including industrial issues. Clothing is considered one of the basic requirements for human life, and the history of the textile industry is as old as human civilization. Fabric is considered a main element for human clothing and is also used in many industrial products. Natural elements such as wool, cotton, a composite of polyester, or nylon can be used to create a textile fabric. The textile industry employs advanced machinery to produce this fabric, and any imperfections are identified during the inspection stage. The conventional approach to inspecting fabric quality involves relying on manual human efforts. The market value of fabric is determined by the frequency of defects present, and the price rises proportionally with the number of defects detected. When a defect is discovered, the production process is halted, and the machine operator records the details of the defect, along with its location.

The main drawbacks associated with manual inspections are as follows:
(1) training of individuals is required to make them fabric inspectors.
(2) Due to human carelessness, small defects can be overlooked while major defects can be identified.
(3) Locating fabric defects requires a significant amount of human effort.
(4) Fabric inspectors find it challenging to sustain their attention on the production process for more than 10 minutes, which could result in decreased production efficiency.

Research indicates that humans have an accuracy rate of 60-75% in identifying fabric defects, and any such defects lead to increased product pricing due to wastage.It is advisable to implement automated processes to detect fabric defects during production to reduce labor costs.

Computer simulations are used for this purpose, and textile products are refined as a result, resulting in better inspection quality. In the textile business, computer vision and digital image processing are critical for this inspection process. Fabric inspection takes place in real-time during the production process, and computer vision and digital image processing techniques are utilized for automated inspection within the textile industry. The defects are caused by different reasons and can be classified as major, minor, or critical defects (depending on the severity of the defects. Broken pick ends, float, holes, stitches, knots, loose threads, starting lines, oil stains and marks, bad selvage, double pick, snarls, cracks, and smashes are some of the prominent and commonly occurring fabric defects. A hole is classified as a major defect that is caused by many reasons such as by a broken needle or a defective machine. Oil stains are mainly caused due to excessive oil from machinery. Multiple netting is a minor defect caused when multiple broken threads are combined. A Broken end appears in the fabric when warp yarns break during weaving. When variations in yarn arise, thick and thin bar defects emerge. A Broken weft appears when weaving filling yarn is broken. When the weft insertion process deviates from a predetermined pattern, the Wrong weft defect can occur in weaving. There exist various categories and classification methods for fabric defects, including typical defects and classifications based on the color of the fabric. This paper goes into great depth about grayscale fabric defect detection algorithms and classification models. Most computer vision algorithms are designed for grayscale images and use different feature extraction approaches to create discriminative image representations. Other than this, grayscale image processing can extract descriptors more easily as compared to color images and grayscale image processing can reduce computational complexity.

II. Approaches

2.1 Related Works

This part offers a review of the literature on some fabric defect detection techniques. The following groups can be used to classify these methods:

2.1.1 Color-based Approaches

Color is utilized in multiple applications within computer vision and digital image processing that employ the visible spectrum. In different fabric defect detection-based approaches, color is extracted as an essential visual feature. Numerous research attempts have been undertaken from various perspectives to improve the accuracy and efficiency of FDD.; however, FDD remains a challenging task for complicated textures. Zhang et al. claimed the visual saliency of defective fabric image regions by contending that visual color differences exist between defective and non-defective local regions of fabric images.

Furthermore, the defective regions are not distributed throughout the picture; they are concentrated in a small area. Based on these findings, the authors suggested determining a pixel's defective value using an integrated color dissimilarity and positional similarity. To improve the reliability and robustness of the findings, multiscale dissimilarity analysis is used to improve the contrast between the defective and non-defective areas. Experiments are conducted using MATLAB R2014a on an Intel Core processor with 6 GB RAM and 3.2 GHz frequency. The experimental findings obtained with various fabric images outperformed the state-of-the-art outcomes for complicated patterns. However, the suggested saliency method's effectiveness for box-patterned and motif-based images could not be determined.

2.1.2 Model-Based Approach

The textures present in an image can be defined by predetermined parameters that constitute an aleatory or deterministic model. Although these methods are very complex and computationally expensive, they may be adequate for images with non-uniform patterns.

The autoregressive model and Gaussian Markov random field are some of the methods that constitute this type of approach. These models can sometimes become very complex and computationally expensive. Autoregressive models were utilized by McCormick and Jayaramamurthy [24] to generate a variety of fabric textures and then compare them to pre-existing textures. Cohen et al. [25] modeled the defect-free fabric with a Gaussian Markov random field model and compared it to the test image fabrics to detect the fabric defects.

2.1.3 E-Texture-Based Approach

Texture analysis, which is widely used in various computer vision application areas, refers to the characterization of regions in an image based on their texture content. Liang et al. suggested an intelligent integrated system for evaluating the surface appearance of yarn. For feature extraction, three methods are used: an attention-driven method is used with saliency maps for fault detection and wavelet texture features, and various statistical measures are used to create the appearance description of the yarn surface.

The fuzzy ARTMAP neural network (NN) is used to acquire features for yarn surface quality grading and classification. To achieve the best classification performance, a comparison of the fuzzy ARTMAP, backpropagation NN, and SVM is performed.

III. Proposed Methodology

The sub-modules that make up our defect detection system include pre-processing and defect object segmentation.

3.1 Pre-processing

This step involves utilizing an image filtering technique to improve the quality of the image.

3.1.1 Image filtering

Image contrast can be increased via histogram equalization, a computer image processing technique. It accomplishes this by effectively spreading out the most common intensity values or expanding the intensity range of the image. This allows for a contrast boost in locations with low local contrast. Below are the stages involved in histogram equalization.

Following are the steps involved in histogram equalization.
Step 1: Acquire the input image.
Step 2: Create an image histogram.
Step 3: Calculate the image's local minima.
Step 4: The histogram is divided using the local minima.

Step 5: the histogram's individual segments should be assigned their own grayscale values.
Step 6: Equalize each partition's histogram.

3.1.2 Defect object segmentation

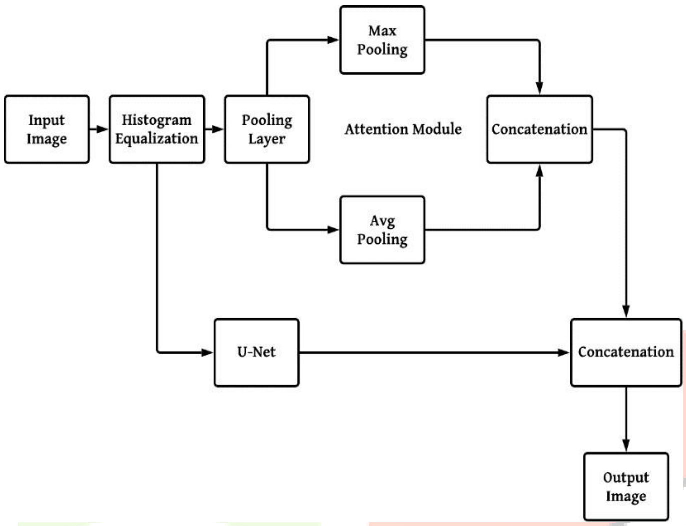
For defect segmentation, the U-Net method is introduced. The context information is passed to the higher feature map through the skip connection between the contracting path and the expansive path in U-Net, and pixel-to-pixel mapping is achieved by discarding all full connection layers.

3.1.3 Attention Mechanism

The mental process of concentrating on specific things while disregarding others is referred to as attention. The attention mechanism enables the classification algorithm to pay closer attention to some of the image's more discriminative local regions, resulting in improved model classification accuracy in complicated scenarios. Skip-connection utilizes the attention technique to address the issue of minor faults that may go unnoticed during the segmentation of certain fabric images.

The attention technique is used to explicitly model the dependencies between feature channels. It's implemented in the CU-skip-connect Net's feature to reduce the number of redundant features by suppressing the typical response of disconnected regions.

IV. Block Diagram



Block Diagram for Fabric Defect Detection

The dataset used is a combination of different fabric defects along with some of the real-time fabric images that were collected by us. The input to the system is an image of a fabric image that can be defective or defect free. After the image is taken as an input a preprocessing technique namely histogram equalization is applied to it. A technique in computer image processing that enhances the contrast of images is histogram equalization.U-net architecture is used for detecting defects in fabrics. A convolutional network architecture called u-net, which achieves high accuracy and processing speed, is utilized for image segmentation. U-net consists of different pooling layers such as max pooling and average pooling layers.

The U-net architecture is combined with the attention mechanism to achieve more accuracy. The attention mechanism enables the classification algorithm to pay closer attention to some of the image's more discriminative local regions, resulting in improved model classification accuracy in complicated scenarios.

V. IMPLEMENTATION & FUTURE WORK

5.1 Implementation

5.2 Future Work

Many researchers have done remarkable research in this field of defect detection and had proposed a variety of different detection algorithms concentrating on improving different types of defects, as fabric detection has grown increasingly vital over time. Insufficient detection of faults can result in a loss for the textile industry. Therefore, it is important to introduce new techniques and methods to increase the efficiency and usability of such systems. Hence, we propose this system and conclude that combining a U-Net architecture with a deep learning architecture can be an effective method for detecting fabric defections.
This can match the demands of the detection of defects in fabrics and delivers an effective engineering solution for the detection of defects in fabrics.

VI. CONCLUSION & REFERENCES

6.1 Conclusion

The textile industry's fabric defect detection techniques have been reviewed and summarized in this article. Based on literature, the method of relying solely on manual human inspection is insufficient and ineffective in fulfilling the present requirements of the textile industry. The current requirement is that the inspection process be done using some industrial automation to improve the quality and lower the production cost of the finished textile product. Computer vision and digital image processing can provide a foundation for filling this business void. Eleven subgroups were used as performance criteria for discussing the methods of fabric defect detection. The fundamental theme of each approach is discussed with advantages and disadvantages, and the study is summarized using a tabular representation. The pictorial representation is used in the review piece to provide an overview of the common study models for fabric defect detection. The image benchmarks used in each study model are thoroughly discussed.

A significant study has been reported to detect using texture, frequency domain, GLCM, feature fusion, sparse feature representation, image morphology, and deep learning-based approaches, according to this review. The primary prerequisite for any defect model is to sort the defective region of textile fabric. The current trends are shifted to the use of deep learning models that require high computational costs for training and a lot of training data. Color and texture feature fusion with deep learning could be a potential future direction. Real-time defect detection remains an ongoing research area in this field, and only a limited number of research models have been proposed for real-time applications.

The textile industry is likely to be interested in defect detection using small handheld devices that require less computational power in the future. According to this review, the research models based on fabric defect detection are assessed using various image benchmarks made by users based on their needs. Except for the TILDA textile dataset, one of the limitations of existing research is the scarcity of publicly accessible datasets. It will be good if some common image benchmarks will be created and shared at public repertoires so that researchers can use them as standards for further research. This will allow researchers to compare their findings to determine the most effective strategy. All of these are possible future research directions for automated fabric defect detection.

6.2 References

[1] A. Latif, A. Rasheed, U. Sajid, et al., "Content-based image retrieval and feature extraction: a comprehensive review," Mathematical Problems in Engineering, vol. 2019, Article ID 9658350, 2019.

[2] Y. Li, H. Luo, M. Yu, G. Jiang, and H. Cong, “Fabric defect detection algorithm using RDPSO-based optimal Gabor filter,” The Journal of the Textile Institute, vol. 110, no. 4, pp. 487–495, 2019.

[3]P. Dario, S. Kolhe, and P. Patil, “A review of automatic fabric defect detection techniques,” Advances in Computational Research, vol. 1, no. 2, pp. 18–29, 2009.

[4]W. Wong and J. Jiang, “Computer vision techniques for detecting fabric defects,” in Applications of Computer Vision in Fashion and Textiles, Elsevier, Amsterdam, Netherlands, 2018.

[5]T. Czimmermann, G. Ciuti, M. Milazzo, et al., "Visual-based defect detection and classification approaches for industrial applications-a survey," Sensors, vol. 20, no. 5, p. 1459, 2020.

[6]E. W. T. Ngai, S. Peng, P. Alexander, and K. K. L. Moon, “Decision support and intelligent systems in the textile and apparel supply chain: an academic review of research articles,” Expert Systems with Applications, vol. 41, no. 1, pp. 81–91, 2014.

[7]K. Hanbay, M. F. Talu, and Ö. F. Ö F.ay/, “Fabric defect detection systems and methods-A systematic literature review,” Optik, vol. 127, no. 24, pp. 11960–11973, 2016.