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Fabric Defect Detection Using Transfer Learning

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***Abstract:** Transfer learning in fabric defect detection involves utilizing pre-trained deep learning models on a large dataset, typically from a different domain, and fine-tuning them on a smaller dataset that is specific to fabric defects. By leveraging transfer learning, the limitations of limited annotated data for fabric defect detection can be overcome by utilizing the knowledge gained from a more extensive and diverse dataset. The pre-trained model's learned features are adjusted to recognize specific fabric defect patterns, resulting in more accurate and efficient defect detection. This approach reduces the reliance on a massive labelled dataset for training, which is particularly beneficial in industrial applications where obtaining a vast amount of annotated fabric defect images may be challenging. Ultimately, transfer learning enhances the model's ability to generalize and detect fabric defects with higher precision, thereby contributing to improved quality control in textile manufacturing processes.*

***Keywords:** Fabric Defect Detection, Textile Quality Control, Manufacturing, Textile Industry.*

1. INTRODUCTION

Fabric defect detection is of utmost importance in modern manufacturing, as it ensures the quality of textile products. However, traditional methods have limitations when it comes to dealing with the intricate patterns and various types of defects found in fabrics. To overcome these challenges, the integration of adaptive neural networks offers a promising solution. By utilizing machine learning, these networks can dynamically adjust and optimize their parameters based on the specific characteristics of the input data. This innovative approach has the potential to greatly improve the accuracy and efficiency of fabric defect detection systems, ultimately leading to the production of high-quality textiles in a more automated and dependable manner.

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1.1 Fabric Defect Detection

Figure 1. Fabric Defect Detection

1.2 Textile Quality Control

In the domain of textile production, guaranteeing the creation of impeccable fabrics is an essential element in upholding quality benchmarks. The process of identifying and categorizing flaws or abnormalities in textile materials, known as fabric defect detection, plays a crucial role in accomplishing this objective. Thanks to technological progress, especially in computer vision and machine learning, novel solutions have emerged to automate and improve the precision of defect detection. These advancements enable manufacturers to implement effective quality control measures, minimizing human mistakes and elevating the overall product quality in the ever-changing and competitive textile industry.

1.3 Manufacturing

Manufacturing serves as the foundation of worldwide economic progress, encompassing a wide range of processes that convert raw materials into finished products. It is a dynamic and evolving sector that not only fosters innovation but also plays a crucial role in job creation and technological advancement. From traditional assembly lines to state-of-the-art automated facilities, the manufacturing industry continuously adjusts to meet the demands of a constantly changing market. Efficiency, sustainability, and quality control are essential considerations in modern manufacturing, with technological advancements like robotics, artificial intelligence, and smart systems reshaping the industry. As manufacturers strive to optimize production, reduce expenses, and improve product quality, the field of manufacturing remains a fundamental driver of progress, influencing global economies and shaping the future of industries worldwide.

1.4 Textile Industry

The textile industry plays a crucial role in the global economy, serving as a diverse and essential pillar. It intertwines various intricate processes such as fiber production, yarn formation, fabric weaving, and garment manufacturing. While rooted in ancient craftsmanship, the modern textile industry has adapted to technological advancements to meet the ever-changing demands of fashion, functionality, and sustainability. From the cultivation of cotton to the utilization of high-tech textile mills, this industry encompasses a vast supply chain that significantly contributes to employment and international trade. In today's environmentally conscious era, the textile industry faces both challenges and opportunities as it strives to balance mass

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production with eco-friendly practices and explores new possibilities in materials and design. As a powerful influencer of trends and consumer lifestyles, the textile industry not only plays a vital role in global commerce but also reflects the dynamic shifts in culture, technology, and the environment.

2. LITERATURE REVIEW

2.1. A Method for Detecting Fabric Defects Using Deep Learning Techniques.

Qiang Liu [1] et.al. Have presented a challenging task in the fabric industry, which is fabric defect detection. The complexity of fabric defects in terms of their shapes and variety has made this task difficult. Although several methods have been proposed to address this issue, they have shown low detection speed and accuracy. However, YOLOv4, a classic deep learning method and end-to-end target detection algorithm, has rapidly evolved and demonstrated promising performance in various industries. In this paper, an improved version of the YOLOv4 algorithm is proposed specifically for fabric defect detection, aiming to achieve higher accuracy. The key enhancement lies in the adoption of a new SPP structure that utilizes Soft Pool instead of Max Pool. By incorporating three Soft Pools, the improved YOLOv4 algorithm effectively processes the feature map, thereby reducing the negative side effects of the SPP structure and enhancing detection accuracy. The improved SPP structure is applied to the three outputs of the Backbone. To ensure successful input into the subsequent PANet, the network structure is enhanced by adding a series of convolution layers after the SPP structure, which reduces the channel numbers of the feature map to an appropriate value.

2.2. Fabric Defect Detection with Deep Learning and False Negative Reduction

Tomás Almeida [2] et.al. Have presented in their research the significance of quality control in fabric production companies. Failure to detect defects in fabrics can lead to financial losses and damage to the company's reputation. In traditional systems, the inspection accuracy ranges from 60% to 75%. To address this issue and reduce costs, the paper proposes a fast and automated defect detection system that can be supplemented with operator decision-making. The system utilizes a custom Convolutional Neural Network (CNN) for defect detection and incorporates over 50 defect types in the training process to ensure a well-generalized system. Moreover, to mitigate the higher cost associated with undetected defects (False Negatives - FN), the proposed system employs FN reduction methods. During testing, the system achieved an average accuracy of 75% in automatic mode. However, when the FN reduction method was applied with operator intervention, the average accuracy increased to 95%. These results highlight the system's ability to accurately detect various defect types while maintaining speed and computational simplicity.

2.3. Cnns Enable Pixel-Wise Fabric Defect Detection without Labeled Training Data

Surface inspection is an essential step in fabric quality control, but it poses challenges due to the various types of defects, diverse fabric textures, and the need for fast detection. In this paper, Zhen Wang [3] et.al. Propose a lightweight deep learning model for fabric defect segmentation. The model takes a fabric image as input and produces a binary image as output. Typically, deep learning models require a large amount of data to update parameters. However, fabric defects are unpredictable, making it difficult to collect a sufficient amount of data. Unlike other models, the proposed method is a supervised network that does not require manually labeled samples for training. Instead, a fake sample generator is designed to simulate defect images using defect-free fabric images. The proposed model is trained using these fake samples and validated using real samples. Experimental results demonstrate that training the model with fake data is effective and achieves high segmentation accuracy on real fabric samples. Additionally, a loss function is introduced to address the imbalance between the number of background pixels and defective pixels in the fabric image.

2.4. An Algorithm for Detecting Fabric Defects Based on Sparse Dictionary Learning is Proposed, Which is Universal and Adaptive in Nature.

Xuejuan Kang [4] et.al. Have presented a novel approach in their research paper to address the challenge of fabric defect detection, considering the complex diversity of fabric texture and defects. While existing methods can only detect a single type of fabric defect, our proposed algorithm aims to overcome this limitation by offering a universal and adaptive defect detection solution based on dictionary learning. To enhance the accuracy of defect detection, we first segment the defect-free image based on the complexity of fabric texture and the brightness and darkness of the background. This segmentation process helps in achieving a more balanced image. Subsequently, we create a random dictionary by selecting feature columns from the image joint matrix, which effectively captures the essential fabric texture and background information. This random dictionary replaces the conventional over-complete and fixed dictionaries, making our algorithm more versatile.

2.5. A Big Data Perspective on Crop Management through Data Analytics.

Nabila Cherie [5] et.al. Have proposed in their system that recent advancements in Information and Communication Technologies (ICT) have had a significant impact on various sectors of the global economy. The emergence of Digital Agriculture is a direct result of the widespread availability of digital devices and advancements in artificial intelligence (AI) and data science. This innovative approach to agriculture introduces processes that enhance productivity, efficiency, and environmental sustainability. By utilizing advanced digital devices and data science, extensive agricultural datasets can be collected and analyzed, empowering farmers, agronomists, and professionals to make more informed decisions and gain a deeper understanding of farming tasks. This paper provides a comprehensive review of data mining techniques specifically applied in the context of digital agriculture, with a focus on crop yield management and monitoring. It also explores various existing works that utilize data analytics in the field of agriculture.

Related Work

The process of manually inspecting textiles is a time-consuming and expensive method. However, advancements in technology have provided a solution to this problem through the development of automatic systems for textile inspection. Despite this, jacquard fabrics pose a unique challenge due to their complex and seemingly random patterns, which can be difficult for these systems to analyze. Previous studies on jacquard fabrics have primarily focused on simple patterns, neglecting the intricacies of more complex designs. This research paper

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introduces a new and innovative approach to detecting defects in jacquard-patterned fabrics. The detection models presented in this paper are specifically designed to handle fabrics with complex patterns. Since there is a lack of available databases for jacquard fabrics, we have compiled our own novel dataset and conducted experiments using it. Our dataset consists of plain, undyed jacquard fabrics with various complex patterns. In this study, we have utilized and tested multiple deep learning models, incorporating image pre-processing techniques and convolutional neural networks (CNNs) for unsupervised defect detection. Additionally, we have employed multispectral imaging, which combines normal (RGB) and near-infrared (NIR) imaging, to enhance the accuracy of our system. We propose two systems: a semi-manual system that utilizes a simple CNN network to operate on individual patterns, and an integrated automated system that employs state-of-the-art CNN architectures to analyze the entire dataset without prior pattern specification. To enhance the features of the images, we have preprocessed them using contrast-limited adaptive Histogram Equalization (CLAHE).

3. METHODOLOGY

The primary objective of the proposed system is to implement a sophisticated framework for detecting fabric defects using transfer learning. Initially, the system loads a dataset comprising images of fabrics with various defects. To ensure optimal model training, data pre-processing techniques are utilized to enhance the dataset's quality and suitability. Subsequently, feature selection is employed to extract pertinent attributes from the data. The crux of the system involves training and testing a deep learning model specifically designed for fabric defect detection, with a particular focus on leveraging transfer learning. By fine-tuning a pre-existing model using the fabric defect dataset, the system capitalizes on the knowledge acquired from a broader context, thereby enhancing its ability to accurately identify fabric defects. This approach not only enhances detection accuracy but also reduces the need for an extensive labelled dataset. Consequently, the proposed system effectively tackles the challenges associated with fabric defect detection by harnessing the power of transfer learning, offering a robust and efficient solution for quality control in textile manufacturing processes.

4. MODULE DESCRIPTION

4.1. Load Data

The system in this module retrieves the necessary data for detecting fabric defects. This process may involve obtaining images or data samples that contain information about fabrics and their defects. The data is typically divided into training and testing sets to develop and evaluate the model. In the textile fabric context, rare anomalies can occur, which can compromise the quality of the fabrics. Therefore, it is crucial to detect these defects in certain scenarios. The images have a size of either 32x32 or 64x64, and the classes for the defects include 'good', 'colour', 'cut', 'hole', 'thread', and 'metal contamination'. Additionally, there are eight different rotations available, ranging from 0 to 140 degrees in increments of 20 degrees. Both a train and test dataset are provided, consisting of randomly generated patches. The source images in the train and test datasets do not overlap with each other.

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4.2. Data Preprocessing
Data pre-processing plays a vital role in the machine learning pipeline as it involves the transformation and preparation of raw data for input into the model. This essential step encompasses various tasks, including image resizing, pixel value normalization, handling missing data, and dataset augmentation, all aimed at enhancing the model's robustness.

4.3. Feature Selection
The process of feature selection entails the selection of the most pertinent attributes or characteristics from the dataset for utilization in the model. The objective of this step is to diminish dimensionality and improve the model's performance by concentrating on the most informative features associated with fabric defects.

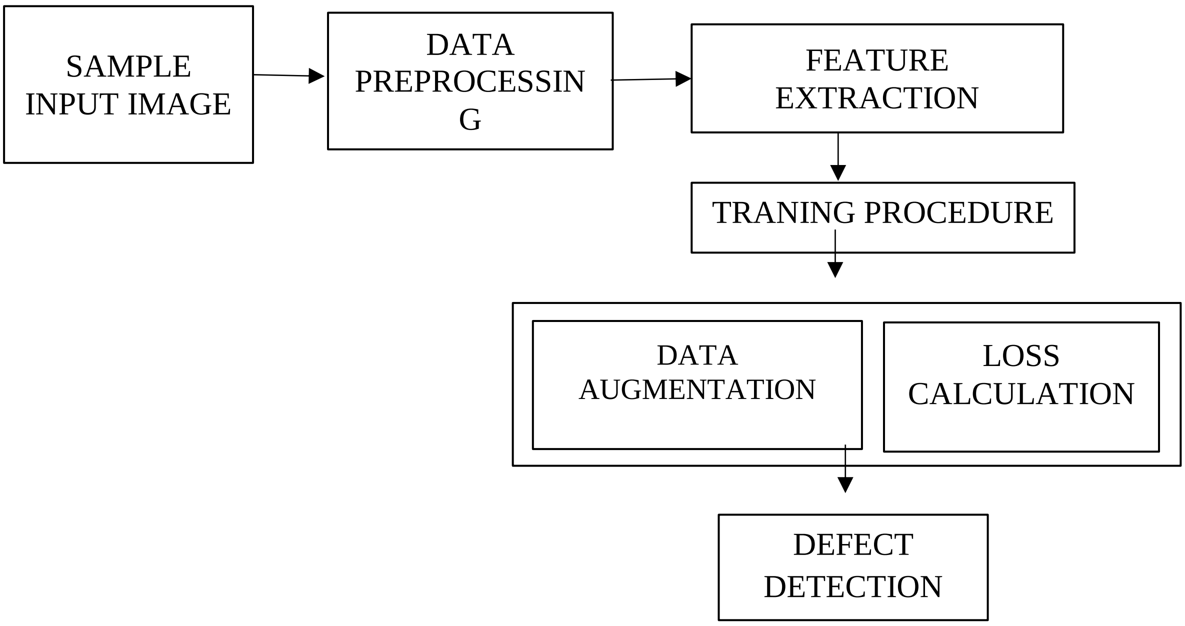

Figure 2. Block diagram

4.4. Training and Testing
During this stage, the machine learning model undergoes training using the prepared dataset. The training process entails fine-tuning the model's parameters to grasp patterns and correlations within the data. Following that, the model is subjected to testing using a distinct dataset to assess its performance and verify its ability to effectively generalize to novel, unseen instances.

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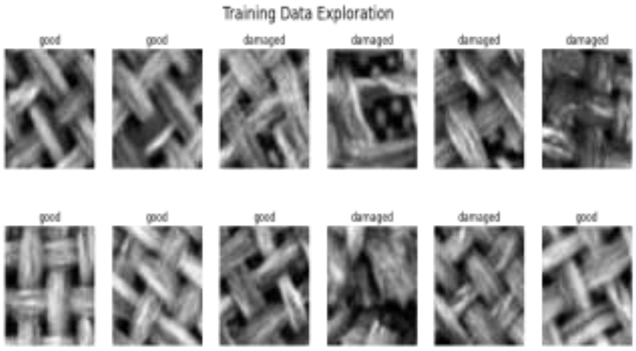

Figure 2. Training data exploration

4.5. Fabric Defect Detection Using Transfer Learning

This module utilizes transfer learning, a method in which a pre-trained model (usually on a large dataset) is adjusted for the specific purpose of detecting fabric defects. The modified model utilizes its previously acquired features to improve its accuracy in identifying fabric defects. Transfer learning is especially beneficial in situations where there is a scarcity of labelled data, as it utilizes knowledge from related domains to enhance the model's performance in the desired task.

5. RESULT AND DISCUSSION

Classes	Count
Damaged	0.83
Good	0.17

Figure 3. Comparison Table

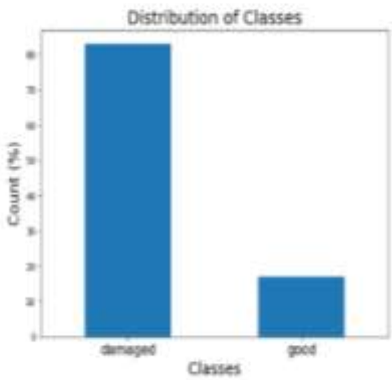

Figure 4. Comparison Graph

In the provided dataset, the distribution of classes reveals that a majority of instances, approximately 83%, belong to the "DAMAGED" class, indicating a prevalent occurrence of damaged samples. Conversely, the "GOOD" class constitutes a smaller proportion, accounting

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for 17% of the dataset. This class distribution suggests an imbalanced dataset, where the model is exposed to significantly more examples of damaged instances compared to good ones. Addressing this class imbalance during model training may be crucial to ensure a balanced and effective learning process, enhancing the model's ability to accurately classify both damaged and good samples in subsequent fabric defect detection tasks.

5.1. Performance Results

- The system was trained and tested on the dataset, demonstrating the ability to accurately detect fabric defects.
- The use of transfer learning improved the detection performance, particularly in scenarios with limited labelled data, by reusing the features learned from a larger dataset.
- Figure 3 and Figure 4 (referenced in the document) show a comparison of the results, indicating that the system was more successful in detecting damaged fabrics due to the imbalance in the dataset.

The study underscores the need for careful consideration of class imbalance during training to ensure the model can effectively differentiate between damaged and non-damaged fabrics.
The key advantage of the transfer learning approach in fabric defect detection is the ability to generalize from a small, domain-specific dataset. By using pre-trained models, the system capitalizes on features learned from other tasks, which reduces the requirement for a large labelled dataset, typically hard to obtain in industrial applications.

The transfer learning method in this case was particularly effective at:

- **Handling complex patterns**: The pre-trained model fine-tuned on the fabric dataset was capable of detecting defects in jacquard and other complex fabric patterns.
- **Reducing computational costs**: Since the model was already trained on a larger dataset, only minimal additional training was needed, which made the system more efficient and faster to deploy.

However, the imbalance in the dataset presented a challenge. With most samples belonging to the "DAMAGED" class, the model could be biased toward over-classifying defects. To mitigate this, techniques like data augmentation or sampling methods could be applied to balance the dataset and improve performance across all classes.
In conclusion, the use of transfer learning demonstrates a promising avenue for improving fabric defect detection systems, contributing to higher efficiency and accuracy in textile quality control processes. Future work should address dataset balancing, real-time processing, and scalability to further enhance the system's performance and applicability.

6. CONCLUSION

In summary, the incorporation of adaptive neural networks into fabric defect detection systems signifies a groundbreaking advancement in modern manufacturing. This innovative approach utilizes machine learning to dynamically adjust and optimize its parameters, effectively addressing the complexities presented by various fabric patterns and defect types. The

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combination of pattern recognition, dynamic adjustment, and data-driven learning empowers these systems to achieve unparalleled levels of accuracy and efficiency. The automation and scalability offered by adaptive neural networks not only streamline the fabric defect detection process but also contribute to the production of top-notch textiles with minimal manual intervention. The success of this technology lies in its continuous learning and adaptation to real-world manufacturing conditions, ensuring reliability and responsiveness. As the industry continues to embrace these advancements, the future holds the promise of even more automated, adaptive, and dependable fabric defect detection systems, representing a significant leap towards excellence in textile manufacturing.

Future Work

Future research in fabric defect detection can prioritize the refinement and expansion of adaptive neural networks to meet the evolving needs of the industry. Efforts can be directed towards improving the adaptability of these systems to a wider thereby increasing their applicability in the textile manufacturing sector. Furthermore, there is potential for exploring advancements in real-time processing and edge computing to enhance the responsiveness and efficiency of defect detection systems. Additionally, the integration of emerging technologies like computer vision and advanced sensors can contribute to a more comprehensive understanding of fabric quality. Collaboration between researchers and industry experts can facilitate the development of standardized datasets and benchmarks for evaluating the performance of fabric defect detection systems. Moreover, there is a need to enhance the interpretability and explain ability of neural network models to instill greater trust in the technology. As the field progresses, it is important to explore eco-friendly and sustainable practices in fabric manufacturing alongside defect detection technologies, making it a prominent area of focus. In conclusion, future work in fabric defect detection should aim for continuous innovation, increased robustness, and practical applicability to ensure the ongoing improvement of textile quality control processes.

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