Neural Network Approach to Classify Defect Types in Cotton Yarns

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Keywords— CNN, yarn defects, textile quality, machine learning, transfer learning

A. *Introduction*

Accurate identification and classification of defects in cotton yarns are crucial for ensuring the quality and consistency of textile products. Defects can lead to compromised fabric quality, reduced durability, and increased production costs.[1] Machine learning techniques like neural networks and support vector machines have been traditionally used for defect detection [2,3], but they struggle with the complex patterns in yarn defects. Recent advances in image processing and deep learning, specifically convolutional neural networks (CNNs), offer promising results for image classification tasks [4], making them suitable for defect identification in cotton yarns. Existing studies have been limited in scope, focusing on specific defects and datasets, hindering the development of a comprehensive defect classification model. This research project aims to address this gap by creating a diverse dataset of various yarn defects, leveraging image processing to improve image quality. The proposed approach utilizes CNNs and transfer learning to build an efficient defect classification model, and its effectiveness will be evaluated against ground truth labels and industry standards. Accordingly, this study presents a solution with potential contributions to the textile industry's quality assurance processes, enhancing product quality and reducing production-related challenges.

B. *Literature review*

Previous research in yarn defect classification has explored various machine learning techniques, including image processing and artificial neural networks (ANNs) such as Probabilistic Neural Networks (PNNs), for identifying defects in cotton yarns. PNNs have been successfully used to classify two types of cotton yarn neps based on image feature extraction, demonstrating accurate results through k-fold cross-validation [5]. Image processing techniques, like Otsu's method, have also been employed to transform yarn images into a binary format, facilitating easy defect identification [5]. Furthermore, ANN and Support Vector Machine (SVM) models have been utilized to predict the quality characteristics of cotton/elastane core yarns, showing promising predictive capabilities [3]. However, despite the achievements of previous studies, limitations persist. Existing research primarily focuses on specific defect types and yarn properties, leaving room for further exploration of more advanced techniques like Convolutional Neural Networks (CNNs) for broader defect classification and enhanced accuracy and efficiency. Additionally, evaluating the performance of CNNs against other methods, such as Random Forest, SVM, k-Nearest Neighbors (k-NN), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), is crucial for identifying the most suitable approach for specific defect detection tasks [6]. Each method has its strengths and weaknesses, making careful consideration of task characteristics and available resources essential for selecting an appropriate defect detection method. This research aims to address these gaps and contribute to the advancement of defect classification in cotton yarns. Convolutional Neural Networks (CNNs) have demonstrated remarkable proficiency in defect detection tasks. These networks employ convolutional layers and filters to extract discriminative features from input images, progressively learning hierarchical representations that encompass escalating levels of complexity [7]. Activation functions such as ReLU introduce non-linearity to the feature maps produced by these filters, thereby amplifying their representational capacity [7]. The utilization of transfer learning involves the integration of pre-trained CNNs, initially trained on extensive datasets, to distill generic features from cotton yarn images. This strategic approach effectively reduces the demand for extensive retraining, facilitating enhanced performance.

C. *Materials and Methods*

A yarn image dataset captured offline was particularly processed using image processing techniques to identify defective and non-defective yarns.[8] Initially the images were manually classified and labeled precisely according to the defects identified. Then this dataset was used and further divided into training and testing sets, adhering to a ratio of 80:20 according to the industry standards, to assess the performance of the proposed Convolutional Neural Network (CNN) model. In constructing the CNN model, a two-stage approach was adopted. The first stage involved building the model from scratch with hyperparameter tuning. Various architectural aspects, such as the number of convolutional layers, image shape, learning rate, dropout rate, filters, kernel size, and pool size, systematically adjust to optimize model performance [9]. The CNN model was fine-tuned to achieve higher accuracy in classifying cotton yarn defects.[10] Image augmentation techniques were utilized to diversify the dataset and improve the model's ability to generalize in the context of limited training samples.[11] Once the models were trained, their performance was evaluated using a separate set of images. Finally, the best model was selected and the defect-wise analysis for best models was performed.

D. Results and Discussion

This research work revolves around enhancing the accuracy of a Convolutional Neural Network (CNN) model for classifying yarn defects. The study involves a two-fold approach: hyperparameter optimization for a CNN model built from scratch and the application of transfer learning techniques using ResNet50, VGG-16, and InceptionV3 pre-trained models. Through meticulous hyperparameter tuning encompassing image shape, convolutional layers, learning rate, filters, kernel size, pool size, and dropout rate, the best parameter configuration yielded a less validation accuracy. To overcome this limitation, transfer learning methods were adopted. Among the pre-trained models, VGG-16 demonstrated robustness with an impressive accuracy across various defect types, while InceptionV3 exhibited exceptionally very high accuracy including both defective and non-defective samples. This highlights the efficacy of transfer learning in capturing intricate patterns and features, resulting in superior accuracy, even with a constrained dataset.

E. Conclusion

This study initially achieved less accuracy through fine-tuning essential parameters, with potential for further enhancements. Strategies like augmenting the dataset, increasing its size and diversity, and adopting advanced architectural elements such as attention mechanisms and residual connections are avenues for heightened performance. Ensemble methods offer supplementary opportunities for accuracy improvement. The incorporation of transfer learning techniques proved highly advantageous, as evidenced by VGG-16 and InceptionV3 models achieving a notable high accuracy on a restricted dataset. These models exhibit suitability for scenarios with limited data, showcasing their potential in mitigating challenges related to dataset constraints. The study's outcomes underscore the effectiveness of transfer learning in addressing such predicaments.

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