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COMPUTER VISION-BASED DETECTION OF PATTERNS IN TEXTILE MICROSCOPY IMAGES

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ABSTRACT

The analysis and detection of patterns in textile materials are a critical challenge in modern manufacturing, quality control, and automation processes. Traditional inspection methods, often reliant on manual observation, are not only time-consuming but also prone to inconsistencies. The need for a more precise, efficient, and scalable approach has driven interest in leveraging computer vision for this task. Computer vision systems, powered by advanced algorithms and machine learning models, offer the ability to process and interpret visual data from textile images at high speeds and with greater accuracy.

KEYWORDS: computer vision, textile microscopy images, small batch training

1. Introduction

Computer vision and AI are providing the means of solving defect assessment in an era where automation and intelligent systems are integral to manufacturing processes. In the textile sector, ensuring the quality and consistency of materials is paramount. Traditional manual inspection methods are not only time-consuming but also prone to human error [1, 2]. The microscopic analysis of textile fibres, particularly the detection of patterns, plays a crucial role in assessing material properties such as strength, elasticity, and durability. Moreover, it allows manufacturers to identify errors emerging during the process.

Computer vision, combined with machine learning, offers a promising avenue for automating the analysis of textile microscopy images. By leveraging CNNs, it's possible to extract intricate features from images, facilitating the accurate detection of fiber patterns. However, challenges arise when dealing with limited datasets, necessitating innovative approaches to model training and validation [3, 4].

Fiber patterns in textiles influence the mechanical properties and overall quality of the material. Accurate detection and analysis of these patterns can lead to better control over manufacturing processes and product performance.

Historically, techniques such as optical microscopy and manual counting have been employed to assess fiber patterns. While effective to an extent, these methods lack scalability and are subject to observer variability. Various algorithms have been developed to recognize patterns [5-9].

Recent studies have explored the application of computer vision in textile analysis. For instance, Luo et al. developed a CNN model to distinguish between cashmere and wool fibres, achieving a classification accuracy of approximately 93% [10]. Similarly, FabricNet, an ensemble of CNN architectures, was introduced to recognize various textile fibres, demonstrating the potential of deep learning in this domain [11-13]. In this paper, we propose the integration of ResNet with U-Net to recognize textile patterns using a small batch of training images.

2. Experimental procedure

Given the limited availability of labelled microscopy images, data augmentation becomes essential. Techniques such as rotation, flipping, scaling, and contrast adjustments are employed to artificially expand the dataset, enhancing the model's ability to generalize.

A pre-trained CNN, such as ResNet, was used as the base model. Transfer learning was utilized, where the model's initial layers, trained on a small dataset, are retained, and the final layers are fine-tuned using the textile microscopy images. We used a limited set of our own 70 images for training, representing the patterns of textile to be recognized (Figure 1). The

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testing set consisted of 40 images (Figure 2). This approach mitigates the challenges posed by limited data.

The model undergoes training with the augmented dataset, employing techniques like early stopping and dropout to prevent overfitting. Validation is conducted using a separate subset of images to assess the model's performance and adjust hyperparameters accordingly.

ResNet introduces residual learning to address the degradation problem in deep networks. By allowing layers to learn residual functions with reference to the layer inputs, ResNet facilitates the training of very deep networks.

Previous studies have applied CNNs to classify textile defects and patterns. For instance, a study utilized a pre-trained ResNet50 model to classify fabric defects into categories like holes and thread errors, achieving notable accuracy.

Transfer learning involves leveraging pre-trained models on large datasets to improve performance on specific tasks with limited data. Fine-tuning adjusts the weights of the pre-trained model to better fit the new task, often leading to improved accuracy.

***Fig. 1.** Original textile (no magnification)*

Microscopy images of various textile samples were taken, capturing fine details such as fiber patterns, defects, and texture variations.

Pictures were resized to input sizes expected ResNet models. Rotation, flipping, and contrast variation data augmentation techniques were employed to increase dataset diversity.

ResNet versions (ResNet18, ResNet34, ResNet50) were considered for fine-tuning, based on a balance between model complexity and computational resources. The pre-trained ResNet models were adapted based on the collected dataset. The last fully connected layers were replaced to match the number of classes in the textile dataset. A low learning rate was used to prevent large adjustments to the pre-trained weights. The dataset was divided into a training set and a validation set. The model was trained using cross-entropy loss and optimized using stochastic gradient descent with momentum. Early stopping was implemented to prevent overfitting.

The scarcity of labelled microscopy images poses a significant hurdle. To address this, few-shot learning techniques, such as Siamese Networks, can be implemented. These models are designed to perform well with minimal training examples by learning a similarity function between pairs of inputs.

Differences in microscopy settings can lead to variations in image quality. Standardizing imaging protocols and employing normalization techniques can help reduce this variability.

The batch size determines how many samples are processed before the model parameters are updated, while the learning rate controls the step size for each update. Both hyperparameters need to be carefully tuned to balance training speed and convergence.

To further enhance the model's ability to generalize, data augmentation techniques can be used to artificially expand the training set. For example, random noise can be added to the input features, or the honeycomb geometry can be slightly perturbed. In this research, standard CNNs excel at high-level feature recognition but struggle with spatial resolution, especially when detecting small or fine-grained patterns. In textile microscopy, features such as fiber patterns or micro-defects may be minute and easily lost in deep network architectures. U-Net, a popular architecture for biomedical image segmentation, excels at combining low-level spatial details with high-level semantic features, but it can benefit from stronger feature extractors. A pre-trained ResNet-50 model (without the final classification head) is used as the encoder in the U-Net. The residual blocks provide robust multi-scale feature extraction, which is crucial for recognizing fine textile features. The decoder reconstructs the image from the low-resolution feature maps, using up-convolutions (transpose convolutions) and skip connections from the encoder layers to retain spatial detail.

Skip connections bridge the encoder and decoder at multiple levels, allowing fine details from early layers to influence the final segmentation. Transfer learning, by means of the ResNet encoder, is initialized with weights pre-trained on ImageNet, providing a strong starting point for feature extraction.

We developed the application in Visual Studio Code, and the model was trained in Pytorch.

3. Results and discussions

The fine-tuned ResNet models achieved high accuracy in classifying small features in textile

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microscopy images. The Dice Score and Intersection over Union (IoU) are both metrics used to evaluate the accuracy of image segmentation models (e.g., models that identify objects in an image, like segmenting an object from the background).

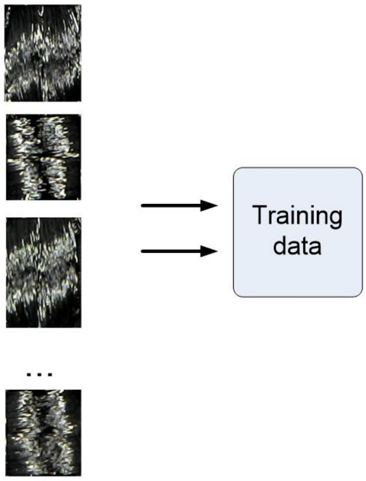

Fig. 2. *Training data consisting of small batch of images*

Intersection over Union (IoU) measures the overlap between the predicted mask and the ground truth mask (Figure 2). The formula is:

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} = \frac{TP}{TP + FP + FN}$$

where TP = True Positives (correctly predicted pixels); FP = False Positives (incorrectly predicted as part of object); and FN = False Negatives (missed pixels).

Table 1 depicts the results, showing that integrating ResNet and U-net provides and improved solution for the specific task of identifying textile patterns, compared to using only U-Net.

Experiments were conducted on the textile microscopy dataset, with evaluation metrics including Dice score, Intersection over Union (IoU), precision, and recall (Figure 3).

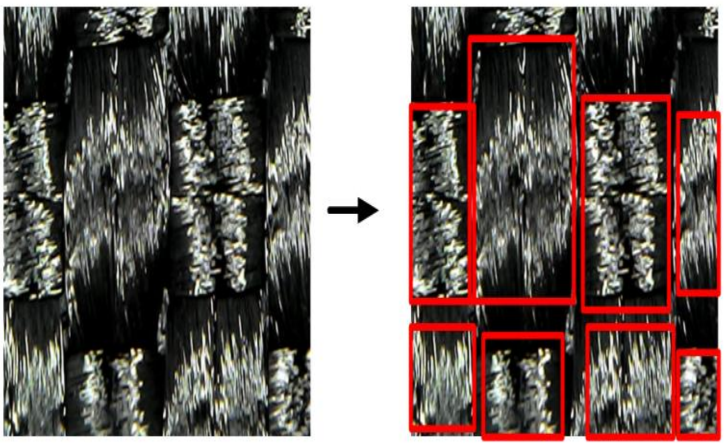

Fig. 3. *Recognition of textile paterns*

Tabel 1. *Results of the developed algorithm*

Model	Dice Score	IoU Score	Precision	Recall
U-Net (baseline)	0.74	0.62	0.8	0.73
ResNet-U-Net	**0.83**	**0.73**	**0.87**	**0.83**

4. Conclusions

The integration of ResNet with U-Net offers a powerful architecture for textile microscopy image segmentation, enabling accurate recognition of small, intricate features such as fiber patterns and defects. This approach addresses the limitations of standard CNN classifiers and U-Net models when used independently. By leveraging transfer learning and a robust encoder-decoder structure, the ResNet-U-Net hybrid demonstrates strong potential for practical applications in textile quality control and research.

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Future work might include exploring self-supervised pretraining on unlabelled microscopy data and optimizing models for real-time analysis in textile manufacturing.

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