Conference Article

An Integrated Deep Learning Framework for Automated Quality Control and Process Optimization in Slasher Indigo Dyeing

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Abstract

This paper presents the development of a multi-step, multi-disciplinary automation framework designed to enhance quality assurance and process control in slasher indigo dyeing machines. The system integrates two complementary subsystems: (1) a real-time yarn defect detection module employing deep learning-based computer vision, and (2) a process optimization module utilizing chromaticity analysis for colour stability and chemical balance control. The defect detection system uses four moving cameras strategically placed across the machine to identify broken yarns and irregular density patterns with high accuracy. The colour monitoring subsystem, developed in collaboration with Agteks, continuously records yarn colour in the CIELAB colour space and recommends corrective pH or reduction agent (Hydro) adjustments when deviations occur.

Experimental results demonstrate a detection accuracy of 92.4%, with significant improvements in production speed, consistency, and operator workload reduction. The proposed system represents a comprehensive step toward fully autonomous dyeing operations aligned with Industry 4.0 objectives.

Keywords: Slasher Indigo, Industry 4.0, Textile Automation, Machine Learning, Deep Learning, Computer Vision

1. Introduction

Automation in textile manufacturing has evolved beyond mechanical process control into data-driven, intelligent systems that integrate sensing, computation, and decision-making. The slasher indigo dyeing process—a critical step in denim production—has traditionally relied on manual inspection and empirical operator adjustments. This introduces variability, reduces throughput, and limits reproducibility. In response to these challenges, this study presents an integrated automation framework for slasher dyeing machines that addresses two primary challenges: real-time defect detection in warp yarns and automated control of dyeing bath chemistry based on live colour feedback. The system combines computer vision, machine learning, and empirical process modelling to transform manual quality monitoring into a self-optimizing digital workflow. The result is a robust, efficient, and operator-friendly approach that supports consistent quality and productivity in industrial dyeing applications.

2. Related Works

The increasing integration of automation, sensing, and artificial intelligence within textile production processes has driven substantial research in both academic and industrial contexts. In the domain of optical colour measurement, Solli et al. [1] proposed spectral estimation methods for colour measurement using consumer-grade digital cameras, while Zhang et al. [2] employed hyperspectral imaging for high-precision colour characterization in printed fabrics. These early contributions established a foundation for quantitative colour monitoring using optical sensors, a concept later extended to process control and material consistency evaluation.

Research on denim defect detection has followed a similar trajectory, evolving from classical image processing methods toward modern deep learning-based approaches. Wang et al. [3] demonstrated the use of Gabor filters to detect weave irregularities and defects in denim fabrics, achieving improved robustness against illumination changes. Celik et al. [4] proposed a real-time inspection system using image analysis to identify common denim defects such as holes, missing warp or weft yarns, stains, and thread flow anomalies. Their work highlighted the industrial relevance of computer vision for continuous production monitoring.

More recently, deep learning-based methods have achieved substantial gains in defect recognition accuracy and adaptability. Talu et al. [5] designed a convolutional neural network (CNN) architecture for loom-fabric inspection, reporting accuracy rates as high as 96.5%. Gu et al. [6] developed an unsupervised segmentation algorithm based on local patch prediction and residual fusion, which enabled defect identification without extensive labelled datasets—a major step toward scalable implementation in data-scarce environments. Similarly, Xu et al. proposed a knowledge-augmented deblurring approach using deep learning to enhance in-situ image quality during yarn inspection, demonstrating the potential for integrated defect correction within the imaging pipeline. These advancements underscore the growing maturity of vision-based textile quality inspection systems.

Despite this growing body of work, the integration of computer vision with active chemical process control in slasher dyeing remains relatively unexplored. Existing solutions typically address visual inspection or mechanical automation in isolation. The system presented in this paper fills this research gap by coupling defect detection and colour-driven chemical regulation within a unified cyber-physical architecture. This approach represents a practical realization of Industry 4.0 principles, transforming optical measurements and deep learning insights into direct, actionable process interventions for improved quality consistency and operational efficiency.

3. Materials and Methods

The automation framework developed for the slasher indigo dyeing machine consists of two tightly integrated subsystems operating under a unified control architecture. The first subsystem is a yarn defect detection module that employs multiple industrial cameras and deep learning algorithms to identify broken yarns and density irregularities in real time. The second subsystem is a colour monitoring and process control module designed to maintain dyeing stability by continuously analysing the CIELAB chromaticity parameters of the yarn surface. Both subsystems are coordinated by a centralized PLC-based automation infrastructure, ensuring seamless communication, deterministic control, and high-speed data handling.

The integration of hardware and software components was designed to achieve robust real-time performance, allowing visual feedback and chemical adjustment mechanisms to operate synchronously with the continuous motion of the slasher dyeing line. The overall system thus combines intelligent image processing, data-driven decision-making, and traditional process control into a hybrid cyber-physical platform.

3.1. Automation Infrastructure

For the automation backbone, a Siemens SIMATIC S7-1515-2 PN programmable logic controller (PLC) was selected. This choice was guided by the need for high processing capacity, sufficient onboard memory, and flexible communication capabilities compatible with modern industrial protocols. The selected CPU includes 6,000 processing elements, 32 GB of load memory, and 3 MB of working memory, providing ample capacity for both control logic and data exchange with external vision systems.

The SIMATIC S7-1500 architecture offers scalability in terms of power, memory, and modular expansion while supporting OPC UA and PROFINET communication. These features ensure interoperability with higher-level systems and readiness for future Industry 4.0 applications. All I/O operations, drive communications, and process control routines are handled through the PLC. Communication between the drives and the operator interface occurs via PROFINET, ensuring deterministic data exchange.

Figure 1 - Siemens S7-1500 PLC

The PLC software utilizes multiple Siemens programming languages—Ladder Diagrams (LAD), Statement List (STL), and Structured Control Language (SCL)—each chosen according to the logic structure and operational requirements of individual control tasks. This hybrid programming approach enhances flexibility, allowing intuitive handling of sequential control processes, mathematical operations, and high-level function blocks

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within a single architecture. As a result, the automation system provides a stable foundation for integrating computer vision modules and executing real-time corrective actions based on vision-derived feedback.

3.2. Yarn Defect Detection System

The defect detection subsystem is based on an array of Daheng MER2-160-227U3C colour USB 3.0 Vision cameras equipped with Sony IMX273 global shutter CMOS sensors [7]. These cameras offer a resolution of 1440×1080 pixels and operate at frame rates up to 227 frames per second (fps). The 1/2.9-inch IMX273 sensor provides a 3.45 µm pixel size, with an 8-bit or 10-bit pixel depth, and supports Bayer RG8 and Bayer RG10 formats. The cameras achieve a signal-to-noise ratio (SNR) of 41 dB and support an adjustable exposure range from 1 µs to 1 s, with gain control between 0–24 dB.

Figure 2 - Daheng MER2-160-227U3C Camera

The use of global shutter sensors minimizes motion artifacts, which is critical for high-speed yarn inspection. Each of the four cameras is mounted at a specific machine section—two in the wet zone and two in the dry zone—covering different optical perspectives. This configuration allows comprehensive monitoring of yarn tension, density, and structural continuity. The camera data are transmitted via high-bandwidth USB 3.0 connections to an industrial PC for on-device image preprocessing before being sent to the central control system.

3.2.1. Deep Learning Architecture

Although classical machine learning algorithms such as k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM) have demonstrated high accuracy in categorical classification tasks [8], they typically require a separate feature extraction stage when applied to image data. Therefore, convolutional neural networks (CNNs) were adopted in this study for their end-to-end feature learning and robust performance in computer vision tasks.

CNNs are a class of deep learning models specifically designed to process and analyse visual data. They automatically learn spatial hierarchies of features from raw pixel inputs,

eliminating the need for manual feature extraction required in traditional machine learning approaches.
The fundamental operation in a CNN is the two-dimensional convolution, expressed as:

$$y_{i,j}^{(k)} = f\left(\sum_{m=1}^{M}\sum_{n=1}^{N} x_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)}\right)$$

where x represents the input feature map, $w^{(k)}$ and $b^{(k)}$ denote the kernel and bias of the k-th filter, respectively, and $f(\cdot)$ is a nonlinear activation function such as ReLU. This operation enables the network to learn local spatial patterns, which are combined across layers to form higher-level abstractions of the input image.

In this study, the ResNet50 architecture was adopted and fine-tuned through transfer learning to leverage pre-trained large-scale visual representations for textile applications. ResNet50 introduces residual connections that facilitate gradient propagation through deep layers, effectively mitigating the vanishing gradient problem and improving model convergence. Transfer learning significantly reduced training time and enhanced generalization by adapting the model's high-level features to the characteristics of the textile dataset.

The trained model was deployed on an embedded inference engine within the industrial PC, enabling real-time analysis of continuous image streams. When a defect is detected, the system immediately issues a visual alarm message via the HMI, allowing operators to intervene without disrupting production. The multi-camera setup, coupled with robust preprocessing and lighting calibration, ensures stability under varying illumination and motion conditions.

3.2.2. Design Evolution and Mechanical Modifications

During prototype development, several iterative design changes were implemented to address limitations identified during early field trials. The four Daheng cameras were originally installed in fixed positions; however, stationary imaging proved insufficient for reliably resolving individual yarns within the yarn band, even at high resolution. To overcome this, each camera was mounted on a linear motion axis, enabling controlled movement across the yarn band width to enhance inspection coverage and detail accuracy.

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Environmental exposure within the dyeing line necessitated further refinements. The cameras were first enclosed in transparent, tunnel-shaped plexiglass housings to prevent contamination from dust and moisture. External cleaning pads were mounted at both ends of each housing to automatically clean the viewing window during camera motion. While this solution effectively protected the optics, it introduced accessibility challenges for maintenance and alignment adjustments.

Figure 3 - Placement of the camera in housing prototype-3

Consequently, the design evolved into a modular form, in which each camera was enclosed in an individual plexiglass box that moved together with the camera along its guide rail. The cleaning pads were repositioned to the endpoints of the motion path, where the housing's front surface was automatically cleaned when the camera reached either limit.

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Figure 4 - Placement of the camera in housing prototype-4

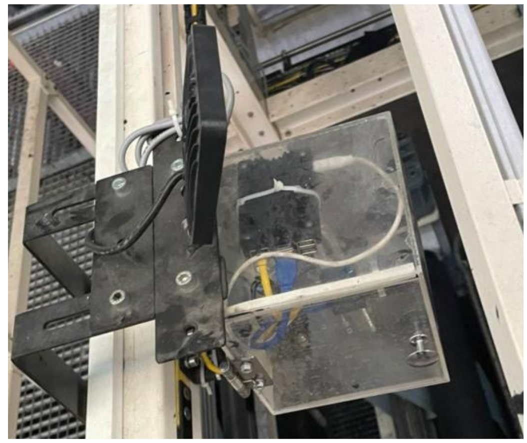

Figure 5 - Placement of the camera in housing prototype-5

This iterative refinement significantly improved the mechanical reliability, maintainability, and image clarity of the vision subsystem. However, the dynamic motion setup introduced cable wear issues, which were later mitigated through the embedded-PC integration discussed in Section 4.

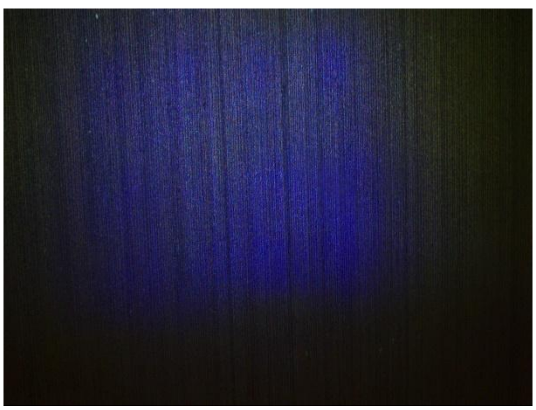

Figure 6 - Image of a non-defect yarn band

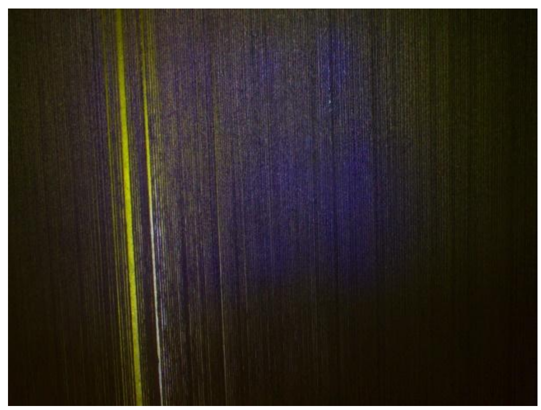

Figure 7 - Image of a defect yarn band

3.3. Colour-Based Process Control System

The second subsystem is dedicated to colour stability and chemical control within the dyeing process. The camera developed for this optical monitoring task employs a custom-designed spectroscopic configuration optimized for near-infrared sensing. The optical path begins with the incident light from the illuminated yarn surface, which is focused through a 25 mm focal length objective lens and directed toward a 30 μm-wide entrance slit. The light is then linearized and dispersed to achieve a spectral resolution of approximately 2.5 nm.

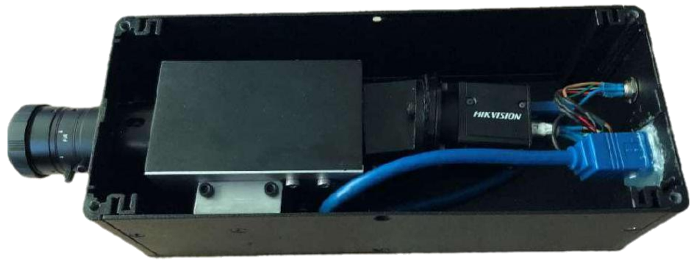

Figure 8 - Agteks Colour Detection Camera System

The detector unit consists of a 320×256-pixel CMOS sensor, with each pixel measuring 30 µm × 30 µm, and operates within a 900–1700 nm spectral range at a frame rate of 344 fps. The system dimensions—310 mm length, 60 mm width, and 65 mm height—make it compact enough for industrial integration near the dyeing bath. This camera system was developed by Agteks and represents a significant innovation in colorimetric process monitoring for textile applications, capable of detecting subtle chromatic variations beyond the visible spectrum.

The camera continuously measures yarn colour and converts spectral data into CIELAB chromaticity parameters (a and b), which correspond to the red–green and yellow–blue colour axes, respectively. Through extensive laboratory calibration, the reference values were determined as a = 1.0203 and b = 0.4381. The real-time colour data are processed by a dedicated software that compares the live readings to these references using a ±0.20 tolerance range. When deviations occur, the system applies empirically established control logic: increasing or decreasing pH and Hydro concentrations depending on whether the yarn shifts toward red/green or yellow/blue.

To ensure robustness, median filtering is applied to the rolling data window to suppress transient noise and outliers. Suggested corrections are limited to ±20% per cycle to prevent overcompensation. Each corrective event is logged and monitored by the PLC, which updates process setpoints and transmits the recommendations to the operator via the HMI. Operators retain full authority to accept, ignore, or automate these adjustments, maintaining a balance between automatic precision and manual oversight.

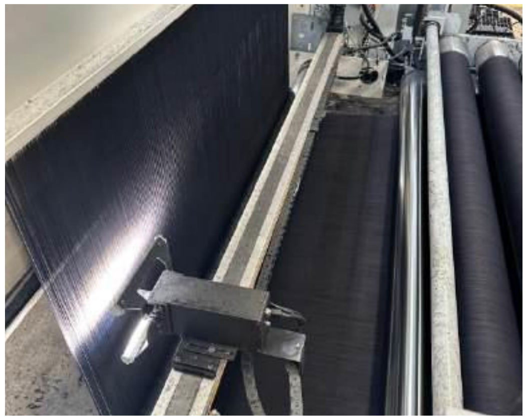

Figure 9 - Placement of the colour detection system

4. Results

Following integration of the software and hardware subsystems, the complete system was deployed on an operational slasher dyeing line. Initial validation involved verifying all electrical and communication links between the cameras, processing units, and PLC. Functional testing confirmed that the image processing module correctly identified yarn defects and that the colour analysis module generated control recommendations consistent with laboratory measurements. During pilot production runs, the system accurately detected and flagged yarn defects in real time, while generating reliable chemical adjustment recommendations derived from live colour data. Operator feedback indicated that the user interface was intuitive and that the automation features significantly reduced manual monitoring requirements.

Certain technical challenges were also identified and resolved during field trials. Uneven illumination conditions initially affected the consistency of defect detection. To mitigate this issue, the LED lighting system was modified to include dimmable functionality, allowing fine-tuned brightness control according to fabric colour and surface properties. Cable wear issues observed during extended operation were resolved by integrating embedded PCs directly into the camera housings, thereby shortening cable lengths and eliminating signal loss. These corrective measures improved both the stability and reliability of the system under industrial operating conditions.

Comprehensive testing demonstrated that the integrated system achieved substantial improvements in both quality control and process efficiency. The defect detection module, built on a fine-tuned ResNet-50 network pretrained on ImageNet, was optimized through extensive trials. A batch size of 16 and 20 training epochs was found optimal for stable convergence and generalization. Training was conducted in two stages:

first, the pretrained layers were frozen and only the classification head (global average pooling, dropout 0.3, and a sigmoid-activated dense layer) was trained using the Adam optimizer with a learning rate of 1×10^{-4}; then, the last 50 layers were unfrozen for fine-tuning with a reduced learning rate (1×10^{-5}), applying early stopping and model checkpointing to prevent overfitting.

Under these conditions, the deep learning model achieved an average classification accuracy of 92.4% and a recall rate of 86.9%, ensuring that most defective yarns were correctly identified in real time. During extended operation, system uptime reached approximately 93%, while manual inspection workloads were reduced by nearly 35%. Furthermore, colour consistency across production batches improved significantly, with only minor deviations observed in CIELAB colour parameters under dynamic production conditions.

Table 1: Performance Metrics of the Deep Learning Model

Metric	Value
Accuracy	92.4%
Precision	88.1%
Sensitivity	85.7%
F1-Score	86.9%
AUC	0.94

The synergy between data-driven defect detection and empirically derived chemical control rules provided a robust and interpretable decision-making framework. This integration bridged laboratory-level precision with practical shop-floor applicability, enabling operators to rely on quantitative feedback while maintaining process flexibility. The modular nature of the system also facilitates future scalability, allowing additional sensors or machine learning models to be integrated as production requirements evolve.

5. Discussion and Conclusion

This study presents a fully integrated computer vision and process control system for automating quality assurance in slasher indigo dyeing. By combining deep learning-based defect detection with real-time chemical correction recommendations, the system advances the textile dyeing process toward a self-regulating and intelligent production paradigm. The proposed framework demonstrates that image-based monitoring and chromaticity-driven chemical control can coexist as part of a unified digital architecture, reducing human intervention while maintaining reliability and precision.

Future research will focus on expanding the dataset to include rare defect types, developing specialized sub-models for complex yarn anomalies, and implementing predictive analytics for proactive process optimization. Further work will also explore cloud-based remote monitoring and adaptive learning mechanisms to continuously enhance system performance. Overall, the developed approach provides a foundation for the digital transformation of traditional dyeing operations and offers a scalable model for next-generation smart textile manufacturing systems.

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