Adopting machine vision

An industrial machine vision system for real-time defect detection in fabric-coated cord using phase analysis and multilayer perceptron classification

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In recent years, the manufacturing sector has undergone a profound transformation driven by the rapid development and integration of digital technologies. This transition, commonly referred to as digital transformation, extends beyond the mere adoption of digital tools and involves the fundamental reconfiguration of industrial processes, production systems and decision-making mechanisms.

The emergence of the Fourth Industrial Revolution, or Industry 4.0, has accelerated this transformation by enabling manufacturing systems to become increasingly interconnected, data driven, autonomous and adaptive.[1] Technologies such as the Internet of Things (IoT), cloud and edge computing, cyber-physical systems (CPS), big data analytics, AI, robotics and advanced sensing technologies constitute the technological foundation of this new industrial paradigm.[2,3]

Together, these technologies enable machines and production systems to continuously acquire, exchange and analyze information, thereby creating the basis for more intelligent and responsive manufacturing environments. Among these technologies, artificial intelligence has emerged as one of the key drivers of Industry 4.0, providing industrial systems with the ability to extract meaningful information from large volumes of complex data and support increasingly autonomous decision-making.

Recent advances in machine learning and deep learning have significantly expanded the applicability of AI in manufacturing, particularly in areas such as predictive maintenance, process optimization, anomaly detection, quality control and intelligent inspection. In parallel with these developments, advances in sensing and computational technologies have made it possible to capture and process visual information at high speed and with increasing accuracy. Consequently, computer vision and image processing have evolved from conventional inspection tools into sophisticated components of intelligent manufacturing systems.[4,5]

By transforming visual data into actionable information, these technologies can bridge the gap between physical production processes and digital decision-making, thereby contributing to the development of more autonomous and data-driven industrial environments.

Within this context, the adoption of machine vision in industrial manufacturing has experienced a growing trend in recent years. Automated visual inspection systems can continuously monitor production processes and evaluate product characteristics with a level of consistency and repeatability that is difficult to achieve through manual inspection alone.

The integration of image processing and machine vision into industrial workflows can enhance confidence in the quality and conformity of final products, reduce production costs associated with defects and rework, and minimize the influence of human error and inspection variability.[6] Moreover, automating repetitive and labor-intensive inspection tasks can reduce dependence on manual operations and allow human resources to be directed toward higher-value activities.

More importantly, the integration of machine vision with AI, IoT, robotics and other Industry 4.0 technologies represents a significant step toward intelligent manufacturing and the realization of next-generation smart factories. In this sense, industrial image processing is not merely a tool for product inspection; rather, it can serve as an essential component of the broader transition toward autonomous, connected and intelligent production systems.

Computer vision applications in the tire industry

The tire manufacturing industry represents a particularly challenging and promising application domain for computer vision and image processing. The highly heterogeneous structure of a tire, the presence of multiple rubber and reinforcement layers, complex surface patterns and the wide variety of possible manufacturing defects make conventional manual inspection both time-consuming and susceptible to subjective judgment. Accordingly, machine vision has increasingly been incorporated into different stages of tire manufacturing, ranging

from the inspection of individual components and semi-finished products to the assessment of the final tire. These applications include surface-defect detection, dimensional and geometric inspection, tread and sidewall analysis, identification of manufacturing abnormalities and non-destructive inspection of internal structures using x-ray imaging. The increasing adoption of such systems reflects a broader transition from operator-dependent quality control toward automated, objective and data-driven inspection.

Early studies demonstrated the feasibility of combining conventional image-processing techniques with statistical and machine-learning methods for tire inspection. For example, Shabbir et al.[7] proposed a method for detecting defects in the cord layer of tires based on the gray-level co-occurrence matrix (GLCM) for feature extraction, followed by Gabor filtering for feature classification and segmentation. Such approaches demonstrated that the texture information contained in tire images could be exploited to distinguish defective regions from normal structures. In another study, Cai et al.[8] developed an automated imaging system for inspecting the metal mold used to engrave tire markings, and for comparing the acquired image with a reference coding model. These early systems are particularly important from an industrial perspective because they illustrate how image-based inspection can be integrated into manufacturing processes to verify not only the physical condition of a tire but also the accuracy and conformity of production-related markings.

Computer vision has also been applied to the inspection of finished tires. Massaro et al.[9] introduced an imaging system for final-product inspection in which a laser-based camera was used to acquire tire images; the acquired data was subsequently processed in a separate processing unit. In subsequent work, the same research group evaluated three image-processing approaches using this inspection architecture and reported their performance for automated tire assessment.[10]

In addition to detecting manufacturing defects, image analysis has been investigated as a means of estimating tire service condition. In one study, texture descriptors were extracted from tire tread images using the gray-level co-occurrence matrix and Gaussian-Markov random fields. The resulting features were then provided to a K-nearest neighbors (KNN) classifier, allowing tires to be categorized into four condition classes: healthy, low wear, moderate wear and severe wear.[11,12]

Such studies demonstrate that machine vision can extend beyond binary quality inspection and provide quantitative information regarding tire condition and remaining service characteristics.

A particularly important research direction concerns the inspection of internal tire structures. Unlike surface defects, many critical manufacturing defects are hidden within the multilayer structure of a tire and therefore cannot be reliably identified using conventional optical imaging. X-ray imaging provides a non-destructive means of visualizing these internal structures and has consequently become an important modality for automated tire inspection.

Several studies have investigated the use of image processing and deep learning for the automatic detection of defects in tire x-ray images.[13] A major challenge in this application is the highly imbalanced distribution of defect-free and defective samples, as defective tires are relatively rare in industrial production. To address this issue, researchers have explored approaches ranging from conventional feature engineering to data augmentation, generative adversarial networks (GANs), transfer learning and unsupervised learning. For example, a GAN-assisted approach was proposed to address class imbalance in tire x-ray defect classification; another study investigated unsupervised defect detection using only defect-free x-ray images for model training.

Recent research indicates a clear shift from handcrafted features and conventional classifiers toward end-to-end deep-learning architectures. Saleh et al.,[14] for instance, developed a transfer-learning-based tire-defect-detection model using a large industrial x-ray dataset containing 3,366 defective and 20,000 defect-free tire images, covering 15 defect types. Their work highlights the practical importance of large-scale industrial datasets and transfer learning in addressing the limited availability of labeled defective samples.

More recently, Xu et al.[15] proposed a YOLOv5-based non-destructive tire-defect-detection framework incorporating dynamic snake convolution, multiscale feature fusion, attention mechanisms and soft-NMS. The proposed architecture was specifically designed to improve the detection of elongated and small defects, such as cord-related abnormalities, which are difficult to identify using conventional convolutional detectors.

Another important development is the application of computer vision to the external surface of tires. Recent work has demonstrated that deep-learning-based systems can detect and characterize defects that vary substantially in both size and appearance. Mignot et al.[16] proposed an automated inspection system based on stereo-photometric imaging and a two-stage multimodal deep-learning framework. The system first performs instance segmentation to localize surface defects, and subsequently estimates their severity by combining visual features with tire-related metadata. The reported defects include

processing stains, demolding marks, foreign particles, air bubbles and geometric deformations, with characteristic dimensions ranging from a few millimeters to several tens of centimeters.

Similarly, research published in 2024 investigated the use of an improved ConvNeXt architecture for detecting small crown defects, addressing practical challenges such as limited datasets, varying tread patterns, low contrast and small defect sizes.

Deep-learning approaches have also been applied specifically to tire cracking and surface deterioration, demonstrating the potential of image-based inspection for monitoring tire condition beyond the manufacturing stage.

The most recent developments suggest that tire inspection systems are moving toward architectures capable of combining local visual features, global contextual information and industrial process knowledge. In 2025, Saleh and Ertunç[17] proposed an attention-based deep-learning framework that combines a vision transformer with a customized attention-based convolutional architecture for tire x-ray defect detection. Notably, the study was conducted using an industrial dataset covering 50 tire designs and 15 defect types; the resulting system was deployed at the Pirelli İzmit automobile tire factory. This represents an important transition from laboratory-level algorithm development toward deployment in an actual tire manufacturing environment.

Other recent research has also focused on explainable AI, addressing the need to make automated inspection decisions more interpretable for industrial quality-control operators. For example, an Xception-based model combined with Grad-CAM was recently applied to foreign-object detection in tire x-ray images, achieving high classification performance while providing visual explanations of the model's decisions.[18]



Figure 1: BarezMind – an integrated platform for tire Industry 4.0

The industrial adoption of these technologies is also evident among major tire manufacturers. Bridgestone, for example, has developed automated tire inspection technologies to replace or complement conventional operator-based visual inspection. The company reports that its automatic inspection system provides repetitive and objective quality assessment with improved precision and repeatability compared with human inspection, while also reducing quality claims. Earlier, Bridgestone introduced its Examation tire assembly system, which combines proprietary information and communication technologies with artificial intelligence and sensor-based measurements across hundreds of quality parameters to control the production process in real time.

These developments illustrate how machine vision and AI are becoming integrated into broader manufacturing architectures rather than being deployed as isolated inspection tools. Michelin has likewise invested in AI- and vision-based technologies across the tire lifecycle. Its automated tire inspection solutions use image acquisition and tire-specific algorithms to assess tire wear, while Michelin's TreadVision system combines AI-powered inspection, robotics and real-time data in the retreading process to identify hidden tire imperfections



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Figure 2: Defect detection algorithm based on phase analysis and an MLP neural network

and improve inspection consistency. Michelin has also developed AI-based computer-vision solutions capable of recognizing tire sidewall information, including tire size, load and speed indices, brand and DOT markings from images.

Together, these industrial examples demonstrate that visual intelligence is increasingly being used not only for conventional defect detection but also for identification, traceability, condition assessment and automated decision-making.

Overall, the evolution of image-processing applications in the tire industry reveals a clear technological progression: from handcrafted texture descriptors and conventional classifiers toward deep neural networks, attention mechanisms, vision transformers, multimodal learning and increasingly autonomous inspection systems. At the same time, the research community and tire manufacturers are confronting similar practical challenges, including the scarcity and imbalance of defective samples, the detection of small and irregular defects, variations among tire designs, complex backgrounds and the need for reliable operation under real production conditions. Consequently, the future of tire inspection is likely to depend not on a single imaging or learning technique but on the integration of multiple imaging modalities, artificial intelligence, industrial sensing, robotics and production data within a unified Industry 4.0 framework.

Proposed machine vision system at Barez Industrial Group

As one of the leading tire manufacturers in Iran and the Middle East, Barez Industrial Group has established a structured roadmap for leveraging the opportunities provided by digital transformation and emerging technologies. In recent years, the company has placed particular emphasis on Industry 4.0, artificial intelligence, the Internet of Things and data-driven manufacturing as key elements of its technological development strategy.

In this direction, Barez has initiated several programs aimed at integrating emerging technologies into its production and decision-making processes. Among these initiatives is the development of an integrated digital platform, referred to as BarezMind, which is designed to continuously monitor the tire manufacturing process, collect and analyze data and transform production data into actionable knowledge across the tire value chain (Figure 1). The development of intelligent inspection systems can therefore be considered an important component of this broader digital transformation strategy, particularly in production stages where rapid and reliable quality assessment is essential.

Within this framework, the present study focuses on the development of an intelligent, real-time, cost-effective and efficient machine-vision system for the automatic detection of surface defects in a tire component known as the fabric-coated cord. The proposed system was designed with particular emphasis on the practical requirements of an industrial production environment, including real-time operation, computational efficiency, affordability and robustness against variations in illumination.

A Raspberry Pi 4 development board and an 8MP camera were employed to implement the imaging and processing unit. For real-time defect detection, a combination of Fourier transform phase analysis and a neural-network-based classification approach was adopted. Initially, potential defective regions were identified using phase analysis. Subsequently, three image features were extracted from each detected region and used as inputs to a multilayer perceptron (MLP) neural network for the final classification of different defect types.

Following parameter estimation and model optimization, the proposed MLP-based system achieved an overall true positive rate (TPR) of 0.98, a false positive rate (FPR) of 0.005 and a false negative rate (FNR) of 0.007 for the detection of the investigated defects. When evaluated separately for each defect category, the system achieved TPR values of 0.957 for baldness, 0.89 for yarn stretching and 0.75 for layer tearing.

The proposed system is particularly valuable for the detection of baldness, which is among the most common defects occurring in the calendering area. Its ability to identify this defect online can substantially improve the accuracy and ease of inspection for production operators while contributing to improved consistency and quality of the final product.

Image-processing method

The overall workflow of the proposed method for detecting surface defects is illustrated in Figure 2. The algorithm consists of four main stages: image preprocessing, preliminary defect detection using phase analysis, feature extraction and final defect classification using an MLP neural network.

During the preprocessing stage, the acquired color image is converted into a grayscale image. The resulting image is then subjected to phase analysis to obtain an initial indication of potential defective regions. Once a candidate defect is identified, three characteristic features are extracted from the corresponding region of the original image. These features are subsequently provided as inputs to the MLP classifier for final identification and classification of the defect.

The feature-extraction region detection process is shown in

Table 2: Performance comparison of the proposed method with Aiger and Talbot[19]

Method	TPR	FPR
Aiger and Talbot[19]	0.73	0.11
This paper	0.988	0.005

Table 1: Performance of the phase-analysis method and MLP neural network

Method	Baldness	Layer tearing	Yarn stretching	Sum.
TPR	0.957	0.75	0.89	0.988
FPR	0.004	0.002	0.001	0.005

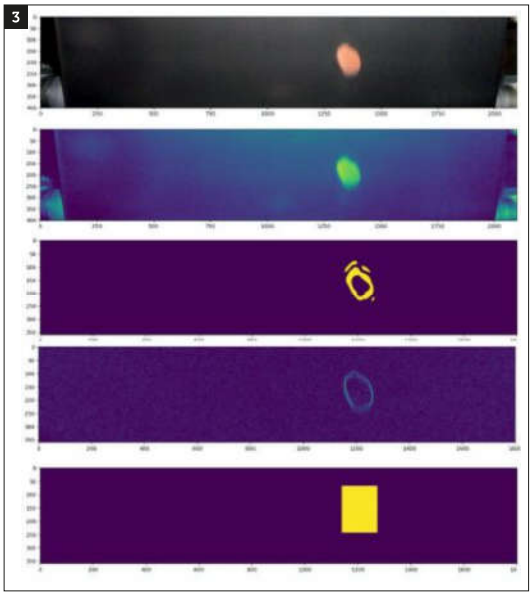


Figure 3. From top to bottom, the sequence includes the original image of the fabric-coated cord, the binary image, the result of the phase-analysis method, the image gradient and the identification of the region selected for feature extraction from the phase-analysis image.

Image dataset acquisition

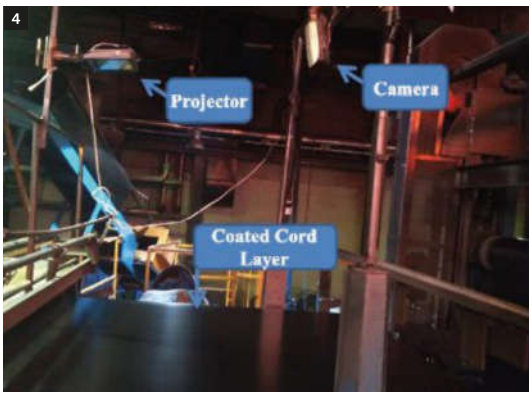
To construct the image dataset, a comprehensive image-acquisition campaign was conducted over a two-week period while the imaging system was installed at an elevated position above the calendering section of the production line. The dataset was collected under realistic industrial operating conditions and included different types of surface defects as well as variations in the ambient illumination. A total of 1,095 images were acquired, including 139 images containing visible defects and 956 defect-free images. The inclusion of images captured under different illumination conditions was intended to increase the robustness of the proposed approach and provide a more representative dataset of the actual production environment.

Figure 4 illustrates the projector and camera configuration. As shown, the projector is mounted vertically and positioned close to the camera. Furthermore, representative images containing defects such as wrinkles, cord-edge defects, baldness and yard stretching are illustrated in Figure 5.

Figure 3: The feature-extraction region detection process

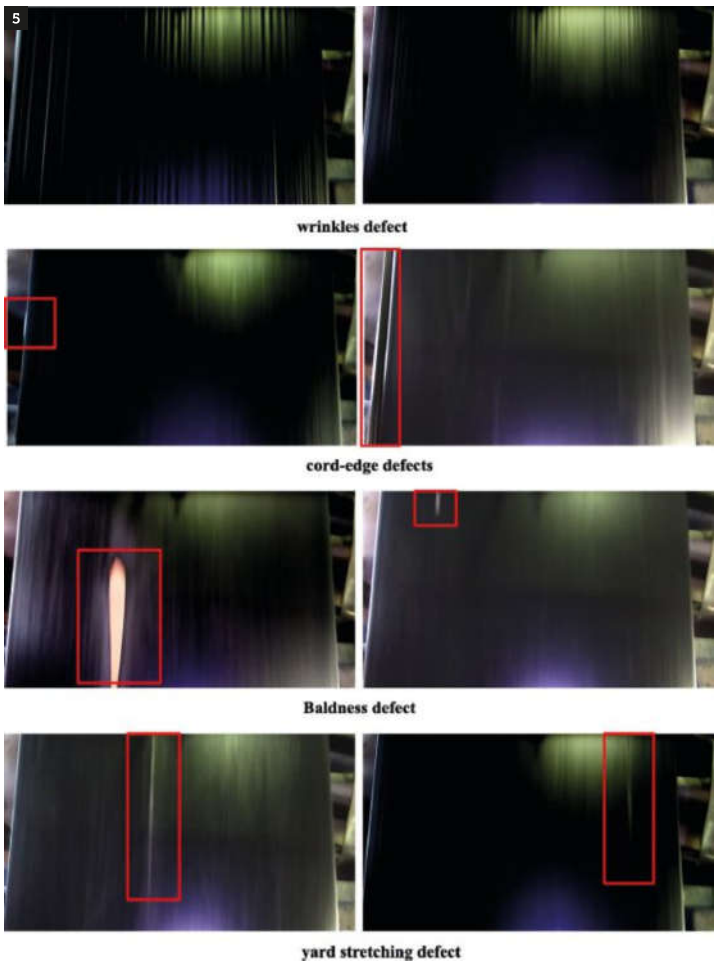
Figure 4: Projector and camera configuration

Figure 5: Representative images containing different defects



Performance of the phase-analysis and MLP-based method

The performance of the proposed method was evaluated for the detection of three major defect categories: baldness, yarn stretching and layer tearing. As presented in Table 1, the proposed method achieved TPR values of 0.988, 0.75 and 0.89 for baldness, layer tearing and yarn stretching, respectively. These results indicate that the proposed approach is particularly effective in detecting baldness, which represents the most frequently occurring defect in the investigated calendering process. Furthermore, as shown in Table 2, the proposed method demonstrated substantially



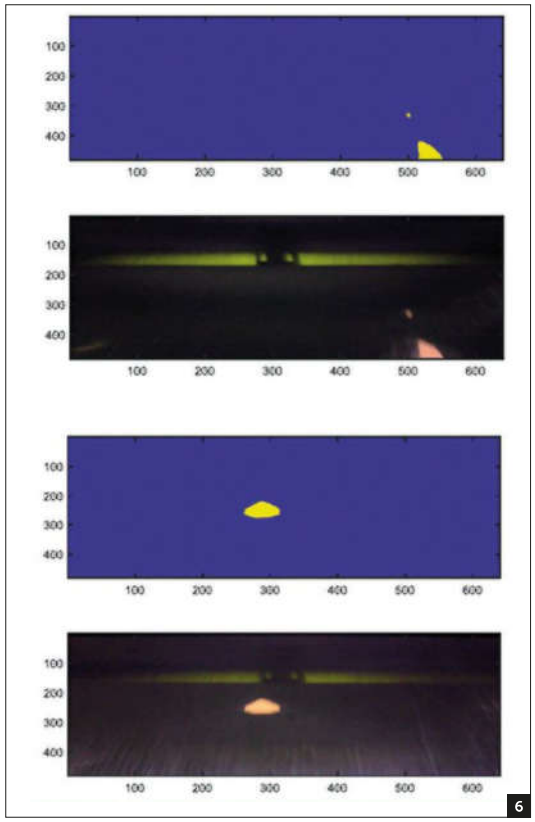


Figure 6: Representative results of baldness defect detection

improved performance compared with the approach reported in Aiger and Talbot.[19] The obtained results confirm the potential of combining phase-based image analysis with a lightweight MLP classifier to develop a real-time industrial inspection system capable of operating with limited computational resources.

Representative results of baldness defect detection are shown in Figure 6. In these images, the upper section presents the detection results, while the lower section shows the corresponding original images. **tire**

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