

Literature Review**Machine Vision-Based Defect Detection for Automotive Brake Pads: A Review of System Components, Image Processing Methods, and Applications**

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Abstract

Automotive brake pads are safety-critical components whose manufacturing quality directly affects braking reliability. Manual inspection is inefficient and susceptible to subjective judgment, whereas machine vision provides a non-contact and automated solution for defect detection. This article reviews machine vision-based inspection of automotive brake pads from three perspectives: system components, image processing methods, and industrial applications. The reviewed technologies include image acquisition hardware, conventional image processing, machine learning, deep learning, and their applications to contour, surface, character, and dimensional inspection. Existing methods are compared in terms of detection capability, interpretability, data dependence, computational cost, environmental robustness, and deployment suitability. The literature shows that conventional image processing remains effective under stable imaging conditions, while deep learning offers stronger feature representation and adaptability but requires representative datasets and greater computing resources. Current challenges include limited public datasets, inconsistent evaluation protocols, sensitivity to industrial variations, and the trade-off between accuracy and real-time performance. Future research should emphasize standardized datasets, lightweight models, few-shot learning, multimodal sensing, and integration with intelligent manufacturing systems. This review provides a reference for the development and industrial deployment of machine vision-based brake-pad inspection.

Keywords

Automotive brake pads, Machine vision, Defect detection, Image processing, Deep learning

1. Introduction

As a foundational component governing vehicular active safety, brake pads dictate the reliability and energy dissipation efficiency of automotive braking assemblies. Throughout the highly repetitive manufacturing process, however, these friction components are inherently susceptible to various quality degradations, structurally categorized into geometric contour anomalies, surface topological defects, and character stamping omissions. The stochastic occurrence of these flaws not only compromises industrial throughput but also introduces catastrophic risks to driving safety. Consequently, establishing zero-defect manufacturing paradigms has emerged as a high-priority mandate in contemporary automotive engineering. Currently, shop-floor defect screening remains heavily reliant on manual visual inspection—a labor-intensive paradigm perpetually plagued by low throughput, high cognitive fatigue, and subjective error rates that fundamentally bottleneck the evolution of fully automated production lines.

To bridge this operational chasm, machine vision has emerged as a pivotal enabler of autonomous industrial cyber-physical systems. Leveraged by rapid advancements in computational intelligence, automated optical inspection has transcended conventional boundaries, achieving widespread deployment across heterogeneous domains including smart metallurgy, precision manufacturing, and automotive diagnostics. Driven by this technological trajectory, extensive scholarly efforts have pioneered innovative machine-vision frameworks tailored for brake pad defect profiling, yielding substantial methodological milestones. Accordingly, this article reviews the development and application of machine vision-based defect detection technologies for automotive brake pads. The scope of the review covers the major components of visual inspection systems, commonly used image processing and intelligent detection methods, and their applications to different categories of brake-pad defects. Specifically, the article first summarizes image acquisition components, including industrial cameras, optical lenses, and illumination devices. It then classifies existing detection methods into conventional image processing, machine learning, and deep learning approaches, and compares their applicability, advantages, and limitations. Subsequently, the applications of these methods to contour, surface, character, and dimensional inspection are discussed. Finally, the principal challenges and future research directions related to datasets, environmental robustness, real-time performance, model generalization, and industrial integration are identified. Research on brake discs and brake calipers is included only when the corresponding defect characteristics, imaging principles, or detection methods provide transferable evidence for brake-pad inspection.

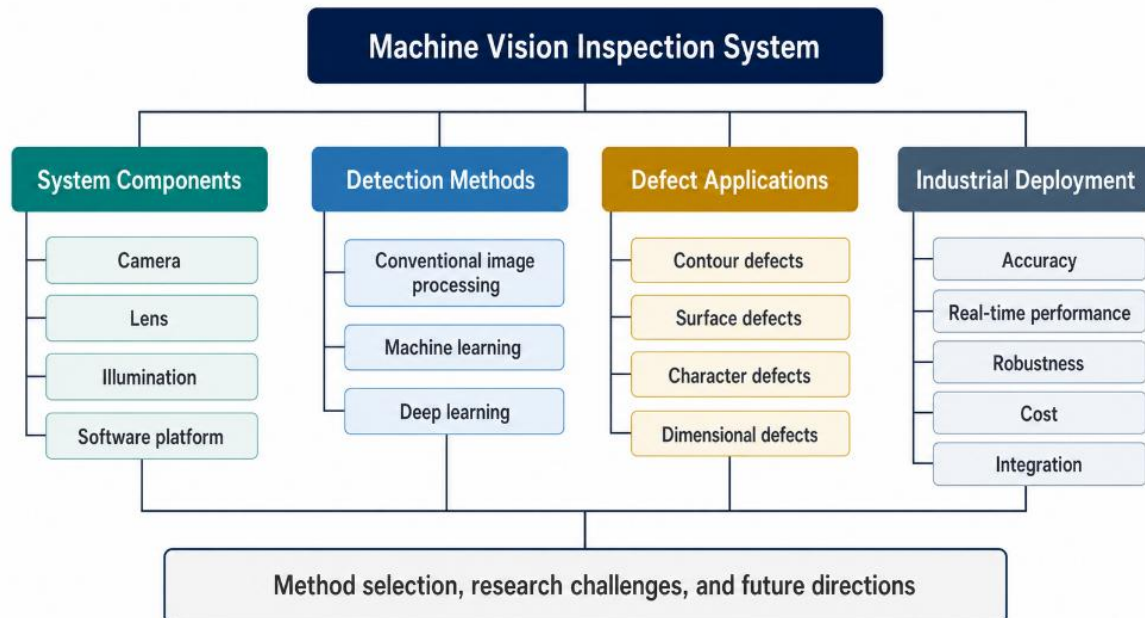
Relevant literature was searched in the Web of Science database using combinations of the keywords “brake pad,” “machine vision,” “defect detection,” “surface defect,” “image processing,” “deep learning,” and “dimensional measurement.” The search covered publications from 2018 to 2026. A total of 45 records were initially identified, of which 40 entered the subsequent screening stage after preliminary checking. Studies were included when they focused directly on brake-pad inspection or

presented machine vision methods transferable from related braking components, such as brake discs and brake calipers. Studies unrelated to visual inspection, lacking sufficient methodological information, or presenting repeated research content were excluded. After screening the titles, abstracts, and full texts, 13 studies were excluded, and 27 publications were finally included in this review.

The contribution of this review lies in the structured synthesis of the available literature rather than in the development of a new detection algorithm. First, the components of brake-pad machine vision inspection systems are organized within a unified framework that links image acquisition, image analysis, defect recognition, and production-line deployment. Second, existing methods are classified according to both their technical principles and their applicable defect categories, enabling a clearer understanding of the relationship between detection tasks and methodological choices. Third, the reviewed approaches are evaluated from multiple practical perspectives, including interpretability, data dependence, computational requirements, environmental robustness, and industrial applicability. Finally, the review identifies common limitations in current studies and summarizes research directions related to benchmark datasets, model generalization, real-time inspection, multimodal sensing, and intelligent manufacturing integration. The overall analytical framework of this review is illustrated in Figure 1.

Figure 1

Analytical framework of this review on machine vision-based defect detection for automotive brake pads



The remainder of this article is organized as follows. Section 2 reviews the research progress in machine vision-based defect detection for automotive brake pads, with attention to the development from conventional image processing to learning-based approaches. Section 3 introduces the principal hardware and software components of brake-pad machine vision inspection systems, including industrial cameras, optical lenses, illumination devices, and vision software platforms. Section 4 summarizes the image processing methods commonly involved in defect inspection, including image

denoising, threshold segmentation, image enhancement, and edge detection. Section 5 discusses the applications of machine vision to contour, character, surface, and dimensional defect inspection. Finally, Section 6 summarizes the principal findings, existing limitations, and future research directions.

2. Research Status of Machine Vision-Based Defect Detection Technology for Automotive Brake Pads

In modern automotive engineering and intelligent manufacturing paradigms, automated visual inspection has emerged as a cornerstone for the quality assurance of braking components. As indispensable friction elements within braking assemblies, brake pads are highly susceptible to diverse morphological anomalies during fabrication and operational service, including micro-cracks, surface abrasion, localized pitting, spalling, character omissions, and foreign contamination. Given that these anomalies directly jeopardize aerodynamic braking stability and vehicular safety, conventional manual inspection—plagued by subjective cognitive bias, low throughput, and poor inter-operator consistency—fails to meet the stringent zero-defect mandates of modern production lines. Consequently, machine vision frameworks have been aggressively integrated into inspection lines, establishing a non-contact, deterministic foundation for autonomous defect regulation.

The historical trajectory of brake pad inspection primarily consolidated around conventional image processing architectures, categorized by empirical feature descriptors and statistical pattern recognition. Initial methodologies relied heavily on color-space segmentation and deterministic template matching to isolate and categorize macroscopic brake pad topologies[1]. To accommodate subtle texture anomalies, handcrafted visual descriptors—predominantly multi-scale wavelet coefficients and intensity histograms—were coupled with hierarchical dichotomy classifiers [2]. Concurrently, mathematical morphology and spatial-domain metrics were implemented to quantify friction surface deterioration and crack propagation scales [3]. While these pioneering methodologies offered high computational efficiency and mathematical interpretability, their detection fidelity remained tightly coupled with empirical parameter tuning, demonstrating vulnerable generalization when subjected to stochastic industrial scene variations.

The paradigm shift toward deep learning has fundamentally decoupled feature engineering from manual heuristics, introducing robust representation capabilities to component inspection. Early neural network deployments verified that data-driven convolutional kernels yield superior discriminative abstractions compared to handcrafted descriptors for heterogeneous surface anomalies [4, 5]. For instance, optimized shallow convolutional topologies (e.g., modified AlexNet variants)[6] successfully demonstrated the efficacy of lightweight models in capturing high-frequency structural anomalies such as cracks and pits [7]. To circumvent the perennial challenge of data scarcity typical of specialized industrial domains, research has advanced into generative data augmentation and few-shot regime

learning, utilizing image self-generation paradigms and meta-learning mechanics to maintain model robustness under highly constrained defect distributions[8]. More recently, the operational scope of deep vision has extended beyond qualitative anomaly classification into sub-pixel dimensional metrology, successfully blending coordinate-regression keypoint detection with anchor-based object detectors for non-contact thickness measurement[9].

This visual inspection methodology shares deep algorithmic and optical commonalities with research executed on adjacent braking system constituents, such as brake discs and calipers, owing to their isomorphic surface matrices and standardized quality assessment protocols. Fast-converging object detection frameworks (e.g., enhanced YOLO architectures) and robust edge-localization operators have been extensively validated for the spatial indexing and defect profiling of brake discs under hostile industrial illumination [6, 10, 11]. Furthermore, the hybridization of meta-heuristic optimization with classical image segmentation[12], alongside machine-learning-driven geometric deformation analysis[13]and PCA-optimized feature extraction for brake calipers [14], collective underscores the versatility of intelligent vision in harsh industrial deployment scenarios.

Despite the demonstrated efficacy of existing vision paradigms in boosting operational consistency, seamless industrial cross-platform deployment remains constrained by a series of systemic bottlenecks. These bottlenecks encompass: (1) the profound scarcity of high-fidelity, public-domain benchmarking datasets; (2) the absence of standardized, cross-industry quantitative evaluation metrics; (3) catastrophic performance degradation under unstable, high-variance industrial illumination; and (4) the inherent structural trade-off between pixel-level localization precision and deterministic real-time inference latency [15-17]. As emphasized across contemporary real-time edge-computing literatures, structural lightweighting, environmental robustness, and predictable execution boundaries dictate the feasibility of practical shop-floor integration [18]. To bridge these operational chasms, subsequent research in machine-vision-based brake pad inspection must systematically gravitate toward edge-compatible lightweight architectures, robust few-shot learning formulations, multi-task joint optimization (simultaneous classification, detection, and metrology), and holistic, intelligent quality semantic evaluation.

2.1. Comparative Analysis of Existing Detection Approaches

Conventional machine vision methods generally identify brake-pad defects through manually designed color, grayscale, contour, texture, or geometric features. Color-space segmentation, thresholding, morphological processing, edge detection, and template matching are computationally efficient and highly interpretable. They are particularly suitable for contour classification, character-region localization, dimensional measurement, and surface-defect extraction when the workpiece position, illumination, and background remain stable. For example, color segmentation combined with

morphological processing and shape-feature matching can efficiently distinguish brake pads with clear appearance and contour differences. However, these methods usually depend on manually selected thresholds and feature parameters. Their performance may decline when the illumination changes, the brake-pad surface produces uneven reflections, the background becomes complex, or the defect has low contrast and irregular morphology[1,15,16].

Hybrid methods combine image enhancement and segmentation with shallow classifiers or neural networks. Such approaches can improve the detection of wear, texture degradation, and low-contrast surface regions while retaining a certain degree of interpretability. For instance, Retinex enhancement, maximum-entropy segmentation, and a fuzzy neural network have been combined for brake-pad wear detection[3]. Compared with purely rule-based methods, hybrid approaches generally provide stronger nonlinear classification ability, but their performance still depends on the quality of handcrafted features and preprocessing results. Their computational requirements are usually higher than those of simple thresholding or template matching, but lower than those of large deep neural networks. They are therefore suitable for moderately complex industrial environments in which defect categories are known and the imaging system can be partially controlled.

Deep learning methods automatically learn hierarchical features and generally provide stronger adaptability to complex textures, irregular defect shapes, and changes in imaging conditions. CNN-based classification methods are suitable for identifying predefined defect categories, whereas object detection and segmentation models can additionally provide defect locations or pixel-level regions. Existing brake-pad studies have explored convolutional networks, improved AlexNet architectures, object detectors, keypoint detection, and synthetic-sample generation[4,5,7–9]. These methods reduce dependence on manually designed features and may perform better than conventional methods when defect appearances vary substantially. Nevertheless, they usually require more labeled data, computational resources, training time, and implementation expertise. Their reliability may also be affected by class imbalance, domain shift, insufficient representation of rare defects, and differences between laboratory and production-line images. Consequently, deep learning is more suitable for complex surface defects and multi-class inspection when representative training data and sufficient computing resources are available, while conventional methods remain competitive for stable and narrowly defined inspection tasks [15,16,23,24].

Table 1

Comparison of machine vision methods for automotive brake-pad inspection

Method category	Main advantages	Main limitations	Suitable applications	References
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Thresholding, morphology, and color segmentation	Simple, interpretable, and computationally efficient	Sensitive to thresholds, illumination changes, and low-contrast defects	Foreground extraction, obvious surface defects, and character-region localization	[1,15]
Edge detection and template matching	Accurate for regular contours and dimensional comparison	Sensitive to pose, scale, reflection, and registration errors	Contour defects, missing structures, character inspection, and dimensional measurement	[1,9,15]
Image processing combined with shallow learning	Moderate data requirements and improved nonlinear classification	Dependent on preprocessing quality and handcrafted features	Wear, pitting, texture degradation, and known defect classes	[3,15]
Deep learning-based classification and detection	Strong feature representation and adaptability to complex defects	Requires labeled data, computing resources, and sufficient model generalization	Cracks, contamination, irregular surface defects, and multi-class inspection	[4,5,7,16,23]
Limited-sample and synthetic-data methods	Suitable for rare defects and insufficient defective samples	May suffer from synthetic-to-real domain gaps and unstable generalization	Rare defects, small-sample inspection, and unknown anomaly detection	[8,24]

As summarized in Table 1, conventional image processing methods are computationally efficient and suitable for structured inspection environments, but their performance is often sensitive to illumination and parameter settings. Learning-based methods provide stronger adaptability to complex and irregular defects, although they require more representative data and computational resources. Therefore, method selection should consider defect characteristics, imaging stability, data availability, real-time requirements, and industrial deployment conditions.

2.2. Experimental Evidence and Reporting Characteristics of Representative Studies

As this article is a review rather than an original experimental study, its conclusions are based on the experimental evidence reported in the reviewed literature. To improve the objectivity and traceability of the analysis, representative studies were further examined in terms of inspection task, data source, dataset scale, image-processing or learning method, evaluation metrics, reported performance, and implementation characteristics. The principal information available from these studies is summarized in Table 2. Only values explicitly reported in the original sources are included; unreported or insufficiently described items are identified accordingly to avoid unsupported cross-study comparisons.

Table 2

Experimental evidence reported in representative brake-pad vision studies

Study	Inspection task and data	Method	Reported performance	Main limitation
Zhao et al. [25]	Shape classification; 98 images covering 54 brake-pad types, including 68 industrial images and 30 augmented images	HSV segmentation, geometric features, and entropy-weighted feature matching	Top-1 accuracy: 95%; Top-2 accuracy: 100%; 110 ms/image	Small and controlled dataset; no external or cross-site validation
Zhao and Wang [3]	Surface-wear detection of automotive cermet brake pads; CCD images	Improved Retinex, maximum-entropy segmentation, and fuzzy neural network	Processing time below 500 ms	Dataset scale, data split, and standardized accuracy metrics were insufficiently described
Wei and Yin [7]	Crack, wear, and dent detection; MSD dataset of approximately 3200 images and SDNET dataset of approximately 2600 images	Improved AlexNet with multi-scale convolution, batch normalization, and global average pooling	MSD: P 97.12%, R 84.75%, 10.53 ms; SDNET: P 95.36%, R 92.82%, 13.71 ms	Datasets are not dedicated automotive brake-pad benchmarks; illumination robustness was not evaluated
Chang et al. [9]	Brake-pad thickness measurement; object and keypoint localization	Object detection, keypoint detection, and geometric measurement	Repeatability error below 0.01 mm	Dataset scale, hardware configuration, and inference time require further reporting

The reported results demonstrate the feasibility of machine vision for brake-pad classification, surface-wear detection, defect recognition, and dimensional measurement. However, these numerical results should not be interpreted as a direct ranking of the corresponding methods. The reviewed studies address different tasks and use different data sources, defect definitions, image resolutions, evaluation metrics, and experimental conditions. Classification accuracy, detection precision and recall, processing time, and measurement repeatability characterize different aspects of system performance and are therefore not directly interchangeable. For example, a high classification accuracy obtained from a small and controlled dataset does not necessarily indicate equivalent robustness under changing illumination, surface reflection, product variation, or previously unseen defects.

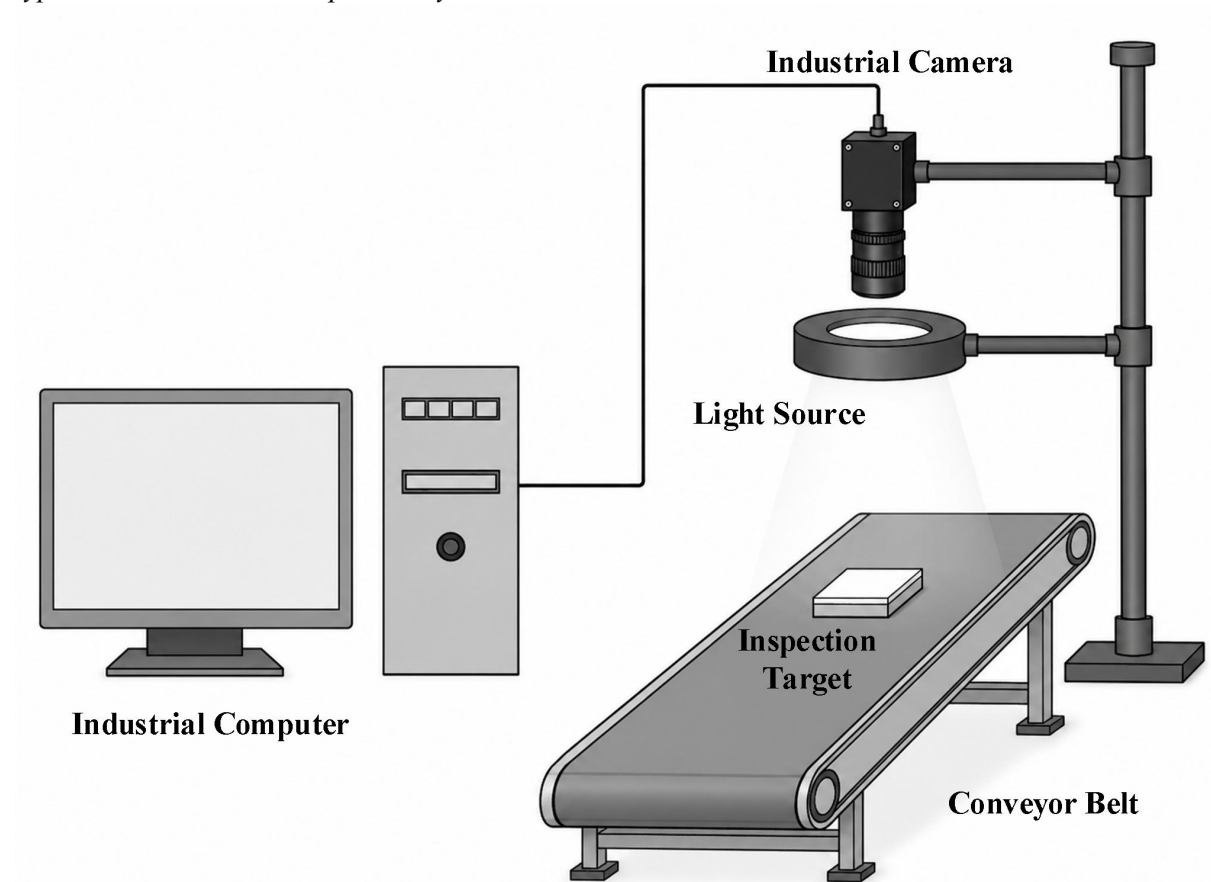
For a more reproducible and meaningful evaluation, the reported metrics should correspond to the inspection task. Classification studies should provide accuracy, precision, recall, F1-score, and confusion matrices; object-detection studies should report precision, recall, mean average precision, and inference speed; segmentation studies should include intersection over union and Dice coefficient; and dimensional-measurement systems should report mean absolute error, root mean square error, maximum error, and repeatability. In addition, dataset size, defect-class distribution, train-validation-test division, image-acquisition conditions, hardware platform, and cross-condition validation should be documented. The inconsistent reporting of these items is an important limitation of the current brake-pad inspection literature.

3. Machine Vision Detection System

A machine vision defect detection system includes a hardware system and a software system. The hardware system mainly completes image acquisition through an image acquisition device, while the software system mainly completes image processing and analysis, extracts image feature information, and identifies and classifies defects on the product surface based on the feature information. A typical machine vision detection system is shown in Fig. 2.

Figure 2

Typical Machine Vision Inspection System



3.1. Hardware System

3.1.1. Camera

As the image acquisition component in machine vision systems, the industrial camera converts optical signals received by the image sensor into computer-readable electrical signals[19]. Currently, CCD and CMOS sensors are the most prevalent imaging technologies in machine vision[20, 21]. Both deploy internal photodiodes to achieve photon-to-charge conversion. Crucially, a CCD sequentially transfers accumulated charges to a unified output structure for charge-to-voltage conversion prior to buffer storage; conversely, a CMOS sensor directly integrates the conversion circuitry on the chip pixel

matrix[22]. Table 3 summarizes the performance comparison between CCD and CMOS to guide camera selection based on specific practical application requirements.

Table 3

Comparison Table of CCD and CMOS

Comparison Item	CCD	CMOS
Design Technology	Single sensor	Photodiode connected with amplifier
Sensitivity	Relatively high	Low
Data Readout Speed	Relatively slow	Over 10 times faster than CCD
Integration Leve	Very low integration	High integration
Noise	Low noise	High noise

3.1.2. Lens

The optical lens collects light from the target object and focuses it onto the image sensor to achieve optical imaging. Since the lens directly affects field of view, magnification, focus, depth of field, and image sharpness, lens selection is a critical step in designing a machine vision inspection system. Crucial specification benchmarks during lens selection encompass resolution, depth of field (DOF), aperture, and focal length. Specifically, telecentric lenses are dedicated designs engineered to eliminate the parallax errors inherent in conventional industrial lenses. Table 4 synthesizes the respective performance merits of telecentric and conventional lenses to facilitate optimal selection based on specific practical application constraints.

Table 4

Comparison of Two Types of Lenses

Comparison Item	Conventional Industrial Lens	Telecentric Lens
Cost	Low cost, practical and widely used	High cost, large size and heavy weight
Magnification	Variable magnification with parallax	Constant magnification without parallax
Application	Imaging of large objects	Metrology and CCD-based measurement

3.1.3. Light Source

The primary objective of the light source in a machine vision system is to acquire high-quality, high-contrast images. Light source evaluation necessitates the careful optimization of uniformity, contrast, illumination angle, and spectral characteristics to guarantee stable system operation and target

performance. Conventional illumination sources deployed in machine vision inspection frameworks predominantly encompass Light-Emitting Diodes (LEDs), fluorescent lamps, halogen lamps, and incandescent lamps. Each illumination paradigm exhibits distinct advantages tailored to specific application scenarios, with a comprehensive performance comparison synthesized in Table 5.

Table 5

Common Light Source Comparison

Light Source	Color	Service Life (h)	Luminance	Features
Incandescent Lamp	White	<2000	Bright	Good color rendering, continuous spectrum, low energy conversion efficiency
Fluorescent Lamp	White with green tint	8000~10000	Bright	Low cost
Halogen Lamp	White with yellow tint	3000~5000	Very bright	High heat generation, relatively low cost
LED Lamp	Red, yellow, green, white, blue	60000	Moderately bright	Fast response speed, flexible structural design, multiple color options

Table 5 indicates that common illumination sources differ in service life, luminance, heat generation, spectral characteristics, and response speed. For brake-pad inspection, the light source should be selected according to surface reflection, defect contrast, acquisition speed, and system stability.

3.2. Machine Vision-Based Defect Detection Software System

In addition to basic digital image processing and spatial analysis algorithms, industrial machine vision software should also support reliable deployment, hardware compatibility, and integration with production-line control systems. Specifically, the human-machine interface [2] requires cognitive workflow optimization to lower operational barriers for non-expert technicians. From the perspective of software deployment, modular tool design and cross-platform compatibility are important for secondary development and migration across different industrial computing environments. For high-throughput industrial applications, compatibility with standard camera interfaces, frame grabbers, and acceleration backends such as multicore CPUs and GPUs can improve image acquisition stability and real-time processing capability.

Commercial machine vision software can be roughly discussed from two perspectives: algorithm-library-oriented development environments and graphical vision-application configuration environments. The first category comprises highly optimized, library-level algorithmic engines represented by MVTec HALCON and LEADTOOLS, which offer extensive mathematical subroutines for complex pixel-level registration and 3D metrology under stringent execution boundaries. The second category encompasses vision-prototyping software environments, typified by Cognex VisionPro and

HexSight, which emphasize granular, drag-and-drop graphical configuration modules to accelerate time-to-market for standard automated optical inspection pipelines.

4. Image Processing Methods for Defect Detection

4.1. Image Denoising

Noise generated during image acquisition may interfere with the extraction of wear boundaries, fine cracks, character edges, and surface textures of brake pads. Therefore, denoising should suppress noise while preserving defect-related structural information. Mean and median filtering are computationally efficient, but excessive smoothing may weaken small defects and edge details. Li applied bilateral filtering to brake-pad wear images before geometric feature extraction and template matching, showing that edge-preserving filtering is more suitable when subsequent inspection depends on contour and texture information [26]. Therefore, the denoising method should be selected according to the noise type, defect scale, and subsequent detection task.

4.2. Image Threshold Segmentation

Threshold segmentation is mainly used to separate brake-pad regions or visible defect areas from the image background. Global thresholding is computationally efficient and is suitable for images with stable illumination and clear foreground–background contrast. When the brake-pad surface exhibits uneven brightness, reflection, or low-contrast wear regions, adaptive or entropy-based thresholding is generally more appropriate. Zhao and Wang [3] combined improved Retinex enhancement with maximum-entropy thresholding to extract worn regions from automotive brake-pad images. This application indicates that the effectiveness of threshold segmentation depends strongly on illumination uniformity and the grayscale contrast between defective and normal regions.

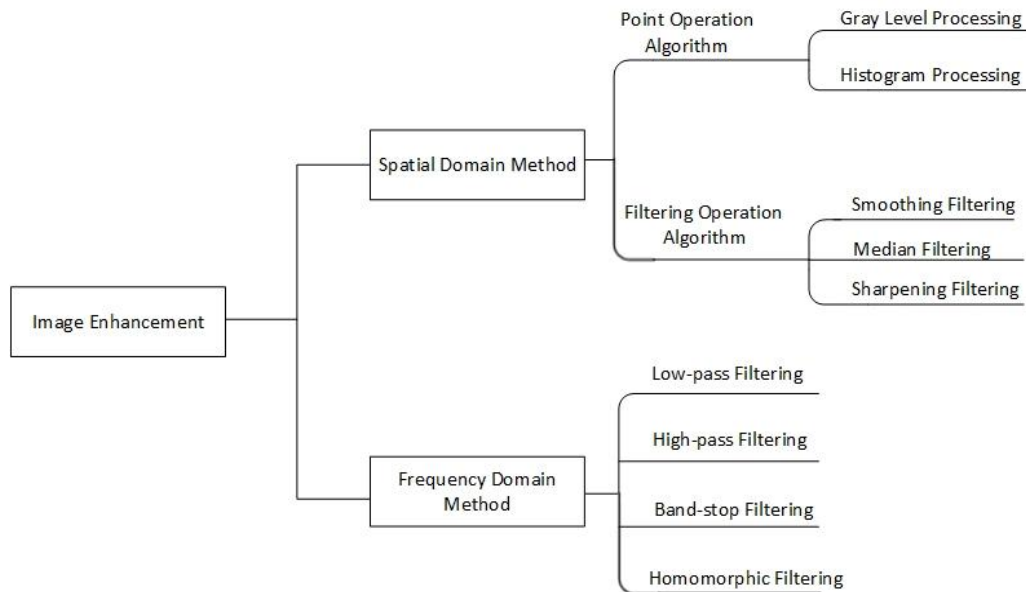
4.3. Image Enhancement

Image enhancement is generally used as a preprocessing step to improve the contrast between defective regions and normal friction materials. Histogram adjustment, sharpening, and Retinex-based processing can enhance weak wear textures and regions affected by non-uniform illumination. However, excessive enhancement may amplify noise or generate artificial boundaries, thereby increasing false detections. In the brake-pad wear inspection method reported by Zhao and Wang [3], improved Retinex enhancement was applied before maximum-entropy segmentation and fuzzy-neural-network recognition. Therefore, image enhancement should be selected according to the target defect and used together with subsequent segmentation or recognition methods rather than treated as an independent detection approach. The classification of commonly used image enhancement methods is shown in Figure 3. Spatial-domain methods directly adjust image pixels to improve contrast and details, whereas

frequency-domain methods modify different frequency components to suppress uneven illumination or enhance defect-related structures.

Figure 3

Classification of image enhancement methods used in machine vision inspection

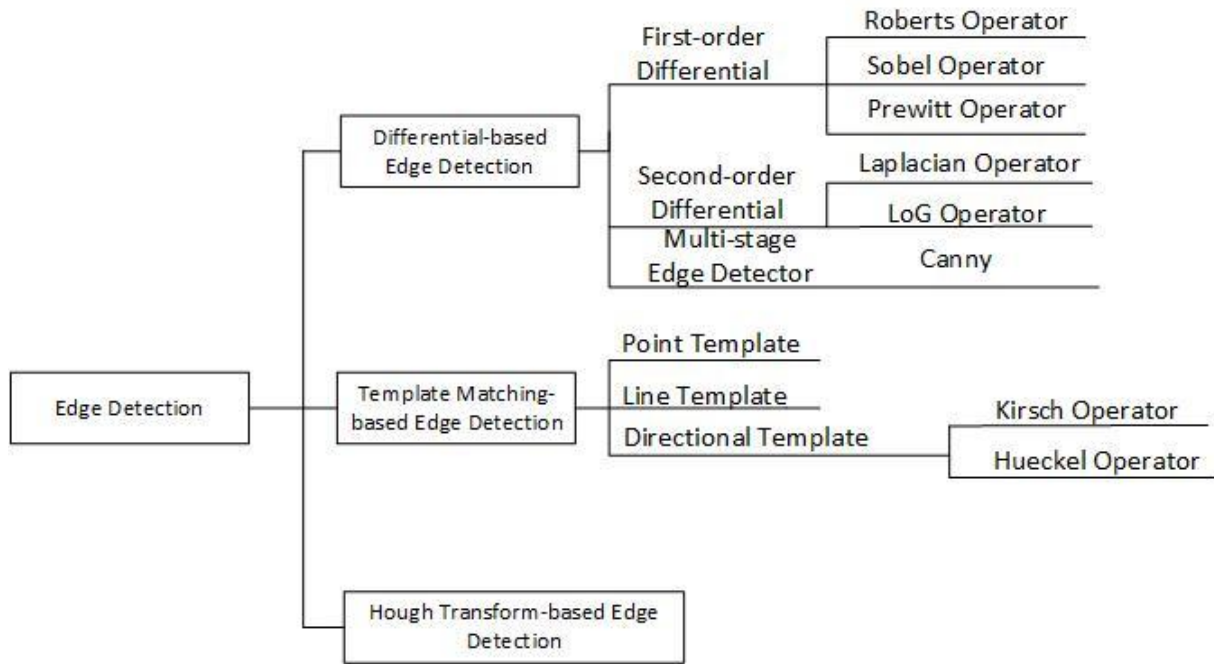


4.4. Image Edge Detection

Edge detection is applicable to brake-pad contour deviations, cracks, missing edges, character boundaries, and dimensional inspection. Roberts, Sobel, and Prewitt are gradient-based first-order operators, whereas Laplacian and LoG are second-order differential operators. The Canny method should be described separately as an optimization-based, multi-stage edge detector that locates edges using the gradient magnitude of a Gaussian-smoothed image [27], rather than being classified as a second-order differential operator. Guo et al. [6] combined an improved Canny operator with probabilistic Hough processing to detect and connect brake-disc scratches. Although the object was a brake disc, the treatment of weak and discontinuous scratch edges provides transferable evidence for brake-pad crack and contour inspection. Edge-based methods remain sensitive to reflection, low contrast, noise, and broken boundaries and are therefore often combined with denoising, morphology, or template matching. The classification of commonly used edge detection methods is shown in Figure 4.

Figure 4

Classification of edge detection methods used in machine vision inspection



5. Machine Vision-Based Defect Detection for Automotive Brake Pads

The following subsections summarize representative inspection procedures and application patterns reported in the literature; no new defect-detection algorithm is proposed in this review.

5.1. Contour Defect Detection

Contour defects are usually detected by utilizing template matching to achieve rapid image alignment, followed by the difference method to realize contour defect identification. The principle of template matching is to extract the basic features of the target during model creation, and search for the target based on the extracted model features within a mixed multi-degree-of-freedom space, subsequently outputting the target position status. In template matching, shape-based template matching algorithms are commonly used for rapid image alignment. Contour defect detection frequently utilizes the image subtraction operation within the difference method. In previously reported machine vision workflows, the brake-pad image is first registered with a reference model, after which image subtraction and connected-component analysis are used to extract candidate contour-defect regions [1,19,20]. The geometric characteristics and positions of these regions can then be analyzed to determine whether contour deviation, missing structures, or excess regions are present. Such methods are computationally efficient and easy to interpret, but their performance may be affected by registration errors, workpiece-position variation, surface reflection, and unstable illumination.

5.2. Character Defect Detection

Character defect detection is commonly implemented through character-region localization, image segmentation, and template-based recognition [19,20]. Utilizing a reference brake pad image as the

structural template, the spatial height or width of the target workpiece is extracted and calibrated against the template dimensions to derive a scaling coefficient, which quantifies the real-world spatial deviations. Concurrently, extracting the centroid coordinates of the workpiece enables the spatial referencing of the character region relative to these calculated offsets. Specifically, the deterministic bounding coordinates of the character zone are formulated by modulating the brake pad center position and the scaling coefficient with the predefined coordinate offset relative to the template center. Following localized region-of-interest (ROI) selection, optimal thresholding is deployed to segment individual character topologies. Leveraging the diverse, pre-trained font databases natively integrated within Halcon, a template-matching procedure compares each isolated character candidate against the reference font models, thereby accomplishing automated character defect inspection. This approach is suitable when the character font, scale, and position are relatively stable, but its performance may decrease under low contrast, character deformation, surface contamination, or positional variation.

5.3. Surface Defect Detection

Surface defects are commonly detected by utilizing image-processing-based defect detection methods. Image-processing-based defect detection methods accomplish defect identification through image feature extraction or template matching algorithms. In image template matching algorithms, element-based matching, gray-level information-based matching, and shape-based matching are the three commonly used methods. Generally, in surface defect detection, shape-based matching is frequently adopted to detect surface anomalies. First, the object to be inspected is determined and segmented from the background. On this basis, a standard image is defined to generate a benchmark template. The image to be inspected is then placed into the model and matched with the standard template. Based on the matching results between the benchmark template and the inspected template, automated identification of brake pad surface defects is achieved.

Template-based methods are effective when the imaging conditions and product appearance are stable. In comparison, learning-based methods provide stronger adaptability to cracks, wear, pits, dents, spalling, and contamination with irregular appearances, although they require representative labeled data and greater computational resources [3–5,7,15,16].

6. Conclusion

This review summarized machine vision-based defect detection for automotive brake pads from the perspectives of research progress, inspection-system configuration, image processing methods, and defect-oriented applications. The reviewed studies cover image acquisition devices, optical and illumination systems, vision software, conventional image processing, learning-based detection methods, and their applications to contour, character, surface, and dimensional inspection. The available literature

indicates that the effectiveness of a brake-pad inspection system depends not only on the selected recognition algorithm but also on the coordinated design of image acquisition, illumination, image preprocessing, feature extraction, defect identification, and production-line integration.

By linking system components, processing methods, and defect-specific tasks, this review further indicates that no single detection approach is universally optimal for all brake-pad defects and production conditions. Conventional image processing methods, including threshold segmentation, edge detection, morphological processing, and template matching, remain effective in structured inspection environments with stable illumination, fixed workpiece positions, and relatively distinct defect features. These methods generally offer clear processing logic, low data dependence, and moderate computational requirements, but their performance is sensitive to parameter settings and environmental variations. In comparison, machine learning and deep learning methods provide stronger feature representation and adaptability for complex textures, irregular defects, and variable imaging conditions. However, their practical performance depends more heavily on representative datasets, annotation quality, computing resources, and model generalization. Therefore, the selection of an inspection method should jointly consider defect type and scale, imaging stability, data availability, detection accuracy, processing speed, system cost, and production-line integration requirements.

Despite the progress achieved, current studies remain constrained by the limited availability of public brake-pad defect datasets, inconsistent defect definitions and evaluation protocols, and insufficient robustness under illumination fluctuations, surface reflections, contamination, product variation, and previously unseen defects. In addition, many studies employ task-specific metrics and provide incomplete information on dataset division, imaging conditions, hardware configuration, and cross-condition testing, which limits reproducibility and direct comparison of the reported performance. Future research should therefore emphasize standardized dataset construction, unified evaluation criteria, lightweight and real-time models, few-shot and unsupervised defect detection, multimodal sensing, and improved cross-domain generalization. Greater attention should also be paid to integrating visual inspection with quality traceability, production-line control, and manufacturing-process adjustment, thereby promoting the transition from isolated defect recognition to closed-loop intelligent quality control. Overall, this review provides a structured basis for selecting detection technologies and developing machine vision inspection systems for automotive brake pads.

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Author contributions

Conceptualization, H.T., H.W., Q.L., and X.L.; methodology, H.T., H.W., Q.L., and X.L.; investigation, H.T., H.W., Q.L., and X.L.; writing—original draft preparation, H.T., H.W., Q.L., and X.L.; writing—

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Data availability

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Declarations**Conflict of interest**

The authors declare that there is no conflict of interest.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

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