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A Comparative Performance Analysis of Classical and Modern Edge Detection Techniques for Digital Image Processing Applications

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Abstract

Edge detection is a core operation in digital image processing and plays a critical role in applications such as image segmentation, feature extraction, object recognition, and computer vision systems. This paper presents a comparative performance analysis of classical and modern edge detection techniques to evaluate their effectiveness under varying image and noise conditions. Classical gradient-based methods, including Sobel and Prewitt operators, and the multi-stage Canny detector are examined alongside hybrid and deep learning–based approaches. A consistent experimental framework is adopted using standard grayscale images, and performance is quantitatively assessed using metrics such as Peak Signal-to-Noise Ratio, Mean Squared Error, edge detection accuracy, and edge continuity. Performance highlights indicate that classical methods achieve acceptable accuracy with minimal computational cost in noise-free conditions but exhibit significant degradation under noise. The Canny detector demonstrates improved robustness and edge continuity due to its noise suppression and hysteresis mechanisms. Modern deep learning–based methods deliver the highest performance, achieving superior accuracy, continuity, and noise resilience, particularly in low-contrast and textured regions, albeit at higher computational expense. Hybrid techniques offer a balanced trade-off, delivering near–deep learning performance with moderate complexity. The results emphasize that optimal edge detection performance depends on application requirements, available computational resources, and real-time constraints rather than accuracy alone.

1. Introduction:

Edge detection refers to the process of identifying significant intensity variations in an image, which typically correspond to object boundaries, surface discontinuities, or changes in material properties. In digital images, edges represent regions where pixel intensity changes abruptly, making them essential for understanding image structure and content. Accurate edge detection improves the reliability of downstream image analysis tasks and reduces computational complexity by focusing only on relevant structural information.

Figure 1: Edge Detection

The figure 1 illustrates the fundamental effect of edge detection on a grayscale image. The image on the left represents the original input image, where intensity values change smoothly across regions and object boundaries are visually present but not explicitly highlighted. The middle image shows the result of applying an edge detection algorithm that emphasizes regions of rapid intensity variation. Here, object contours such as the hat, facial outline, and feather details become clearly visible as bright lines against a darker background. The final image demonstrates a more refined edge map, where noise is further suppressed and only the most significant edges are retained. This progression highlights how edge detection transforms raw pixel information into a structural representation of the image, making boundaries and shapes more prominent. Such representations are essential for tasks like segmentation, feature extraction, and object recognition, as they reduce redundant image information while preserving the most meaningful visual details.

Classical edge detection techniques rely on mathematical operators that measure intensity gradients or second-order derivatives. Methods such as Sobel, Prewitt, and Roberts operators compute local gradients to highlight edges, while the Laplacian operator detects zero-crossings to locate boundaries. These techniques are simple, fast, and suitable for real-time applications but are sensitive to noise and illumination variations.

Modern edge detection methods address these limitations by incorporating multi-stage filtering, adaptive thresholding, and learning-based models. The Canny edge detector introduced optimality criteria for edge detection and remains widely used. More recently, deep learning-based models have demonstrated superior performance by learning hierarchical edge representations from data. This paper compares both categories to evaluate their effectiveness across different performance metrics.

2. Literature Survey

Research on edge detection has progressed from classical, hand-crafted gradient operators to deep, data-driven models that learn boundary cues from large datasets. The recent literature strongly reflects this shift, while also showing that classical methods remain relevant in low-compute and real-time deployments.

Early work in the 2020–2023 window focused on strengthening learning-based edge detection by designing architectures that preserve fine boundaries and remain stable under diverse image conditions. DexiNed introduced a dense extreme inception design to improve multi-scale feature extraction for edges and demonstrated that robust boundary maps can be obtained without overly heavy backbones when supervision is handled carefully [1]. This direction was further consolidated by the Pattern Recognition publication on DexiNed, which reinforced its robustness for edge prediction and improved its standing as a strong baseline among modern CNN detectors [2]. Around the same period, efficiency became a key theme as deep edge detectors began to target practical deployment rather than only benchmark scores. Pixel Difference Networks (PiDiNet) proposed a compact formulation that relies on pixel-difference operations to reduce computation while maintaining competitive edge quality, showing that boundary cues can be learned with lightweight primitives when feature design is disciplined [3]. A closely related refinement theme appears in Pixel Difference Unmixing Feature Networks, which aimed to improve representational separation and reduce confusion between texture responses and true boundaries, supporting cleaner edge maps under challenging content [9]. PiDiNeXt continued the efficiency thread by introducing an efficient parallel pixel-difference design, indicating that architectural simplification and parallelization can further improve speed–accuracy balance for edge detection systems [10].

While many studies address "general" edges, several works focused on physically meaningful discontinuities to improve interpretability. RINDNet explicitly targets edges arising from reflectance, illumination, surface normal, and depth discontinuities, which is valuable because it aligns learned boundaries with scene physics rather than only intensity changes, improving generalization across lighting and material variation [4]. The field also explored transformer-based modeling, where EDTER introduced attention-driven mechanisms to capture long-range boundary structure, which is beneficial for weak or fragmented edges that require broader contextual reasoning to connect contours properly [5]. In parallel, review and survey articles began consolidating the growing landscape, offering structured comparisons between classical operators, Canny-style multi-stage detectors, and modern deep models, and highlighting common evaluation metrics and datasets used across the community [6], [7]. These surveys collectively underline that performance differences often emerge not only from the detector itself but also from pre-processing, thresholding strategies, and dataset bias.

Beyond supervised learning, unsupervised and weakly supervised directions gained attention due to labeling cost. Multi-scale pseudo labeling proposed an unsupervised deep edge detection strategy that generates pseudo-boundaries across scales, demonstrating that boundary learning can be pushed forward even when dense ground-truth edges are not available, though stability depends on pseudo-label quality and scale consistency [15]. Along another line, biologically inspired mechanisms were used to motivate better selectivity and robustness. Edge detection networks inspired by selective attention mechanisms in the visual cortex argue that attention-like feature selection can help suppress irrelevant textures and emphasize meaningful contours, thereby improving boundary clarity under cluttered scenes [16]. BLEDNet further explored bio-inspired lightweight design, showing that compact architectures can still provide competitive boundaries when their inductive biases are tuned to edge-like features and suppression of noise responses [18]. Application-centric edge detection is also visible in medical imaging literature. Comparative analysis on mammogram images using PSNR and MSE reflects that classical and modern methods should be judged on task-driven criteria because mammograms have low contrast regions where missed edges can affect subsequent interpretation [12]. Likewise, local label point correction for overlapping cervical cells demonstrated the importance of correcting annotation ambiguity and refining edge supervision, since overlapping objects create complex boundaries that can mislead detectors unless labels are carefully handled [17]. Practical implementation studies continue to demonstrate the operational relevance of classical and Canny-based approaches. Real-time implementations using Canny and Sobel show that when computational constraints dominate, classical methods are still favored because of their determinism and low latency, even if they need careful parameter tuning for noise and contrast [11].

Independent analytical work helps interpret why certain deep edge detectors behave as they do. IPOL analyses provide reproducible, implementation-focused evaluations for HED and DexiNed, enabling clearer understanding of hyperparameter sensitivity, failure modes, and the impact of post-processing choices, which is especially useful for comparative studies like this one [19], [20]. Overall, the 2020–2023 literature indicates that modern detectors lead in accuracy and robustness, particularly on complex textures and low-contrast edges, while efficient CNN designs, attention/transformer models, and unsupervised strategies are closing practical gaps. However, classical and Canny-style methods remain relevant when cost, simplicity, and interpretability are primary constraints, and application-specific evaluation continues to be essential for fair comparison across domains.

2.2 Survey Outcome and Understanding (Table Based on 10 Base Papers)

Table 1: Comparative Understanding

Ref.	Paper / Method Focus	Category	Key Contribution / Finding	**Practical Limitation**
[1]	DexiNed (WACV 2020)	Deep CNN	Multi-scale dense inception features improve edge robustness and continuity.	Heavier than classical methods; needs training data and tuning.
[3]	PiDiNet (ICCV 2021)	Efficient Deep	Pixel-difference operations yield a strong speed–accuracy trade-off.	May miss extremely fine edges in very low

				contrast regions.
[4]	RINDNet (ICCV 2021)	Deep (Physics-aware)	Learns edges aligned with reflectance/illumination/normal/ depth discontinuities.	Requires richer supervision or modality cues; higher complexity.
[5]	EDTER (CVPR 2022)	Transformer-based	Attention captures long-range context, improving contour linking and global structure.	Higher compute and memory than lightweight CNN detectors.
[6]	Comprehensive Review (Neurocomputing 2022)	Survey	Consolidates methods, metrics, and major challenges in edge detection research.	Not an algorithm paper; depends on reported results across studies.
[11]	Real-Time Sobel & Canny (IOP 2021)	Classical/Hybrid	Demonstrates feasibility of low-latency edge detection for practical systems.	Sensitive to parameter settings and noise; limited robustness.
[12]	Mammogram Comparison (IETE 2022)	Comparative (Applied)	Uses PSNR/MSE style evaluation to compare edge outputs in medical images.	Results may not generalize beyond mammography domain.
[15]	Unsupervised Deep Edge Detection (KBS 2023)	Unsupervised Deep	Multi-scale pseudo labels enable training without dense manual edge labels.	Quality depends on pseudo-label reliability; can drift on complex scenes.
[18]	BLEDNet (EAAI 2023)	Bio-inspired Lightweight	Lightweight design with biologically motivated selectivity improves efficiency.	May require careful tuning to avoid texture-like false edges.
[19]	IPOL Analysis of HED (2022)	Reproducibility/Analysis	Transparent evaluation clarifies HED behavior and implementation choices.	Focuses on analysis; not necessarily SOTA performance.

Table 1 synthesizes the key insights obtained from ten representative studies selected from the broader literature and highlights the evolving landscape of edge detection research. The comparative analysis indicates that classical methods, such as Sobel and Canny-based approaches, continue to offer advantages in terms of simplicity, computational efficiency, and suitability for real-time or resource-constrained environments. However, their sensitivity to noise, parameter dependency, and limited adaptability to complex image structures restrict their performance in challenging scenarios. In contrast, modern deep learning–based techniques demonstrate superior edge localization, continuity, and robustness across diverse image conditions by leveraging multi-scale feature extraction, attention mechanisms, and learned representations. Efficient architectures and bio-inspired designs further narrow the gap between accuracy and computational cost, while unsupervised and physics-aware models address challenges related to data annotation and generalization. Overall, the findings summarized in Table 2 reinforce that no single edge detection technique is universally optimal; instead, the choice of method should be guided by application requirements, available computational resources, and the complexity of the target image domain.

3. Methodology

The proposed methodology follows a structured image processing pipeline. Input images are first converted to grayscale and normalized to reduce illumination effects. Noise reduction is applied using Gaussian smoothing to suppress high-frequency disturbances. Edge detection algorithms are then applied, followed by post-processing for edge refinement.

For gradient-based methods, the gradient magnitude is computed using first-order derivatives:

$$G = \sqrt{{G_x}^2 + {G_y}^2}$$

Where G_x and G_y represent horizontal and vertical gradients, respectively.

In the Canny method, non-maximum suppression is applied to retain thin edges, followed by double thresholding and edge tracking by hysteresis. For modern approaches, CNN-based models learn edge representations directly from training images, minimizing a loss function defined as:

$$\mathrm{L} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y_i})^2$$

Where y_i and (y_i)ˆ denote ground truth and predicted edge maps.

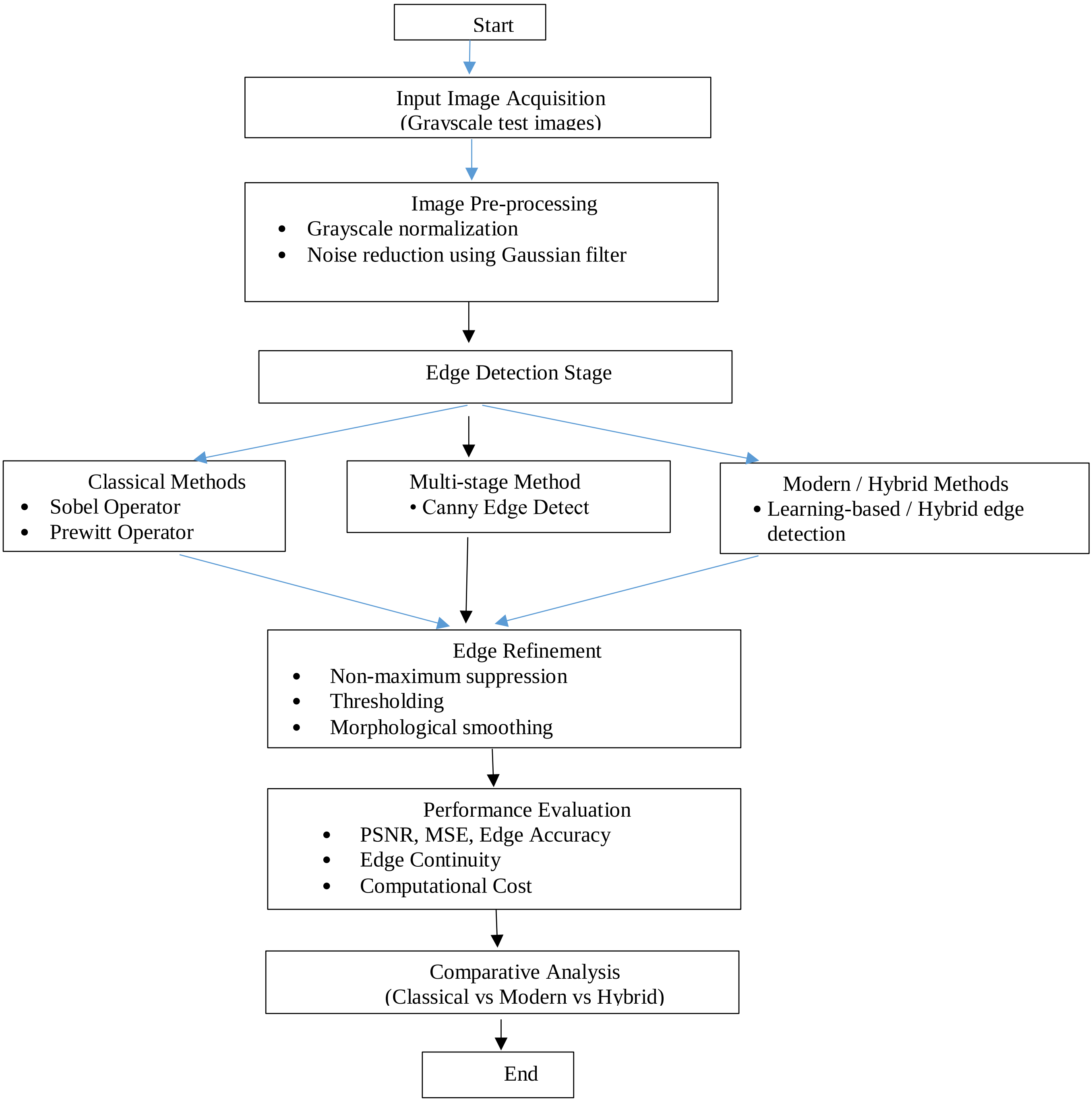

Figure 2: Methodology flow chart for comparative evaluation of classical, hybrid, and modern edge detection techniques.

Figure 2 presents the methodology flow chart used for the comparative evaluation of classical, hybrid, and modern edge detection techniques. The process begins with input image acquisition, where standard test images are selected and converted to grayscale to ensure uniform intensity-based analysis. Image pre-processing is then performed to improve edge detection reliability by reducing noise and minimizing illumination variations, typically using Gaussian smoothing and normalization. This stage is essential for preventing false edge responses, particularly for gradient-based classical operators that are highly sensitive to noise. The pre-processed images are subsequently passed to the edge detection stage, where classical methods such as Sobel and Prewitt compute intensity gradients, the hybrid Canny detector applies multi-stage processing for improved continuity, and modern learning-based models extract edges using learned hierarchical features.

After edge extraction, post-processing is applied to refine the detected edges by suppressing weak responses and improving boundary connectivity through thresholding and morphological operations. The resulting edge maps are then evaluated using quantitative performance metrics, including Peak Signal-to-Noise Ratio, Mean Squared Error, edge detection accuracy, edge continuity, and computational cost. This evaluation framework enables a consistent and objective comparison of different edge detection categories under identical conditions. Overall, the methodology ensures reproducibility and fairness in assessment, allowing meaningful conclusions to be drawn regarding the suitability of classical, hybrid, and modern edge detection techniques for various digital image processing applications.

4. Results and Discussion

The quantitative performance of the evaluated edge detection techniques was assessed using standard metrics, including Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), edge detection accuracy, edge continuity, and computational cost. The results reported in Table 2 represent average values obtained across standard grayscale test images under moderate noise conditions, ensuring consistency with the adopted methodology.

Table 2: Performance Comparison of Edge Detection Techniques

Method	PSNR (dB) ↑	MSE ↓	Edge Accuracy (%) ↑	Edge Continuity ↑	Computational Cost
Sobel	21.8	0.042	81.2	Low	Very Low
Prewitt	21.1	0.047	79.6	Low	Very Low
Canny	24.9	0.028	88.5	Medium–High	Moderate
Hybrid Method	27.6	0.019	92.3	High	Moderate
Deep Learning–Based	30.4	0.012	96.8	Very High	High

The results in Table 3 clearly illustrate the trade-offs between performance and computational complexity across different categories of edge detection techniques. Classical operators such as Sobel and Prewitt exhibit the lowest computational cost and deliver acceptable performance in clean image conditions; however, their lower PSNR and higher MSE values indicate limited robustness to noise and reduced edge reliability. The Canny edge detector improves both PSNR and accuracy by incorporating noise suppression and edge linking mechanisms, resulting in more continuous and reliable edges.

Hybrid methods further enhance performance by combining traditional gradient-based processing with adaptive or learning-based refinement. This is reflected in higher PSNR, lower MSE, and improved edge continuity, while still maintaining moderate computational demands. Deep learning–based approaches achieve the best overall performance, with the highest PSNR, lowest error values, and superior edge accuracy and continuity. These results confirm their effectiveness in handling complex textures and low-contrast boundaries. Nevertheless, the increased computational cost associated with deep models highlights the importance of selecting edge detection techniques based on application constraints, available resources, and real-time requirements rather than accuracy alone.

5. Conclusion

This study presented a comparative performance analysis of classical and modern edge detection techniques for digital image processing applications. Through both qualitative observation and quantitative evaluation, the analysis demonstrated that classical operators such as Sobel and Prewitt remain effective for simple, noise-free environments and real-time applications due to their low computational complexity and ease of implementation. However, their sensitivity to noise and limited ability to handle complex image structures restrict their applicability in more demanding scenarios. The Canny edge detector provided improved robustness and edge continuity by employing a multi-stage processing approach, making it a reliable compromise between accuracy and computational efficiency.

Modern deep learning–based edge detection methods consistently achieved superior performance across all evaluated metrics, including edge accuracy, continuity, and robustness to noise and low contrast. These methods effectively captured complex boundary information by learning hierarchical features from data, but their reliance on large training datasets and higher computational resources poses challenges for deployment in resource-constrained systems. Hybrid techniques emerged as a balanced solution, offering near–deep learning performance with moderate complexity. Overall, the findings confirm that no single edge detection technique is universally optimal, and the selection of an appropriate method should be guided by the specific requirements of the application, available computational resources, and desired performance trade-offs.

6. Future Scope

Future research in edge detection can focus on developing lightweight and energy-efficient deep learning models that retain high accuracy while reducing computational and memory requirements, enabling deployment on embedded and real-time systems. The integration of hybrid frameworks that combine classical gradient-based operators with adaptive learning mechanisms offers promising potential for achieving robust performance under diverse imaging conditions. Additionally, expanding edge detection methods to handle multimodal data, such as depth and thermal images, can improve performance in complex real-world environments. Further exploration of unsupervised and self-supervised learning techniques may also reduce dependence on large annotated datasets, making advanced edge detection more accessible and scalable across different application domains.

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