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Deep Learning Edge Detection for Image Segmentation: Advances and Challenges

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Abstract

This study offers a thorough Systematic Literature Review (SLR) of current advancements in deep learning-based edge detection techniques for picture segmentation. The study is motivated by the shortcomings of conventional edge recognition methods in processing complicated images, especially when there is significant noise, low contrast, and a variety of texture variations. Deep learning techniques are becoming more and more popular because to the growing need for precise picture segmentation in a variety of industries, including autonomous driving and medical imaging. This study examines 32 carefully chosen scientific papers from reliable sources using the PRISMA 2020 technique. The results show a substantial departure from traditional approaches in favor of Transformer-based models, encoder-decoder models like U-Net, and Convolutional Neural Network (CNN)-based architectures that increase edge detection accuracy and consistency. Additionally, it has been demonstrated that combining attention processes with multi-scale feature extraction improves object border accuracy. Nonetheless, issues including the need for sizable labeled datasets, computational complexity, and restricted generalization capacity continue to be major worries. Future trends toward the creation of more effective, flexible, and real-time models are also identified by this study. It is anticipated that the results will be used as a guide for creating more reliable and useful edge detection techniques.

***Keywords**: Edge Detection, Deep Learning, Image Segmentation, Convolutional Neural Network, Systematic Literature Review*

1. Introduction

In applications like object recognition, shape analysis, segmentation, feature extraction, image enhancement, image understanding, compression, and preprocessing, edge detection is an essential approach in image processing and computer vision [1]. In order to extract useful visual information, analyze image structures, and make subsequent computer vision tasks easier, this technique entails locating boundaries or edges between objects or regions [2]. In a variety of application domains, including medical imaging, remote sensing, and autonomous vehicle systems, edge information forms the basis for numerous sophisticated procedures, including picture segmentation, object recognition, and visual analysis [3]. As a result, the effectiveness of the entire image analysis procedure depends on the quality of edge detection [4].

Conventional edge detection techniques like Sobel, Prewitt, and Canny have been applied extensively. Therefore, traditional image edge detection methods are more mature, simple, yet efficient in detecting changes in image intensity [5]. These traditional methods are also considered well-established and are still widely used in various basic image processing studies [6]. Nevertheless, this approach has drawbacks when addressing the complexity of modern images, particularly in conditions involving noise, low contrast, and a wide variety of object shapes and textures[7]. As a result, the edge detection results are often inaccurate and fail to optimally represent the object's boundaries[8].

By capturing high-level representations, our deep learning method significantly improves accuracy and edge detection. Convolutional Neural Network (CNN)-based models are capable of extracting features hierarchically and generating image representations [9], which is more complex than conventional methods [10] and has relatively poorer recognition capabilities for large-scale objects. Convolutional Neural Network (CNN)-based models are capable of extracting features hierarchically and generating more complex image representations than traditional methods [11]. CNN also performs well on various image-based segmentation and object recognition tasks [12]. In addition, encoder–decoder architectures such as U-Net and Transformer-based models have demonstrated superior capabilities in capturing both local and global information, resulting in more accurate and consistent edge detection [13][14]. Various advancements, such as the use of attention mechanisms and multi-scale feature extraction, are also effective in feature extraction and boundary-aware learning, and they also improve the model's performance in handling highly complex images [15].

Nevertheless, there are still several obstacles in the way of using deep learning-based techniques for edge detection. These include the requirement for enormous quantities of labeled data and high computational complexity [16], as a result of the emergence of edge computing devices that execute inference fast and effectively due to the incorporation of hardware accelerators [17]. Furthermore, research is still being done on problems like edge sharpness and noise sensitivity [18]. As a result, numerous novel strategies are still being put out to enhance edge detection quality across a range of image formats [19].

Given these problems, a thorough analysis is required to highlight recent advancements and pinpoint obstacles in the field of deep learning-based edge detection research. Thus, this study's goal is to perform a systematic literature review (SLR) using the PRISMA 2020 methodology [20]. Because it allows for a methodical and controlled literature selection procedure [21], on several papers pertaining to edge detection for image segmentation, the PRISMA technique was employed. The examination of popular model designs, the datasets utilized, the effectiveness of the method, trends, and potential future research directions are the main topics of this paper [22]. It is anticipated that this study's findings will improve knowledge of developments in AI-based edge detection techniques and act as a guide for further investigation [23].

2. Literature Review

A key element of digital image processing, edge detection helps determine object boundaries, which serve as the foundation for image segmentation [1]. The quality of edge detection significantly influences the results of subsequent analyses, as errors in determining object boundaries can impact the accuracy of subsequent processes. As the complexity of image data increases, edge detection methods have evolved significantly from conventional approaches toward deep learning-based methods that are more adaptive and capable of producing more accurate detection results [24].

2.1. Traditional Edge Detection Method

In certain studies, conventional techniques like Sobel, Prewitt, and Canny edge detection are still employed as fundamental methodologies [25]. These methods rely on changes in pixel intensity, but they have limitations when dealing with noise and complex object structures [26]. As a result, their performance tends to be inferior to that of modern methods [1].

2.2. Deep Learning Approach

In contemporary edge detection, deep learning-based techniques in particular, Convolutional Neural Networks (CNNs) have taken the lead [24]. Because CNNs can extract information in a hierarchical fashion, they can identify intricate patterns in photos that conventional techniques are unable to [27]. CNN-based techniques can greatly increase edge detection accuracy when compared to traditional techniques, according to a number of studies [11]. Nevertheless, this method's shortcomings include its high computational cost and need for a substantial quantity of training data [1]. Furthermore, the quality of the dataset employed has a significant impact on the model's performance and its capacity to generalize to new data [18].

2.3. Encoder–Decoder Architecture

Encoder–decoder architectures such as U-Net are widely used in edge detection due to their ability to preserve spatial information through skip connections [13]. This approach enables the integration of low- and high-level features, resulting in more detailed and accurate edge detection [28]. Compared to standard CNNs, U-Net demonstrates better performance in image segmentation, particularly in the medical domain [29]. However, some studies indicate that this architecture has limitations in capturing global context, especially in images with complex structures [13]. Additionally, this model requires significant computational resources, posing a challenge for large-scale implementation [28].

2.4. Transformer and Hybrid Models

Vision Transformer-based models are increasingly being used in edge detection due to their ability to capture global relationships between pixels. This provides an advantage over CNNs, which focus more on local features. Recent research shows that Transformers can improve edge detection accuracy in highly complex images. However, the use of Transformers has drawbacks in the form of very high computational complexity and significant memory requirements [17]. To address this, many studies have developed hybrid models that combine CNNs and Transformers [30]. This approach has proven capable of balancing accuracy and efficiency, although the model design becomes more complex and difficult to implement [14].

2.5. Dataset for edge detection

The datasets used in edge detection research include natural images and medical images [24]. A major challenge that is often encountered is the limited availability of labeled data and variations in annotation quality, which can affect model performance [18].

3. Research Methods

The PRISMA 2020 criteria, which are recommendations for systematic reviews and meta-analyses, were used in this work together with the Systematic Literature Review (SLR) approach. This approach was used to find, assess, and compile pertinent research in an organized, transparent, and methodical way [20][21]. This study focuses on the developments and difficulties associated with using deep learning techniques for edge identification in image segmentation.

3.1. Search Strategy and Data Sources

In order to find, assess, and analyze literature pertinent to the subject of deep learning-based edge detection, this work uses a systematic literature review (SLR) technique. To guarantee transparency and the research's reproducibility, a methodical literature search was carried out in compliance with PRISMA criteria [20]. Well-known scientific resources including Google Scholar, IEEE Xplore, and ScienceDirect provided the primary data. These three sources were chosen due to their abundance of publications on edge computing, image processing, and enhanced intelligence.

Keywords such as “edge detection,” “deep learning edge detection,” “CNN edge detection,” and “guided segmentation edge detection” can be used in the search process with the Boolean operators AND and OR. To ensure the research remains up-to-date, publications are limited to those from 2020–2026 [31]. The inclusion and exclusion criteria were used to perform the literature review. As a result, the sources were distributed as follows: 25.5% from IEEE Xplore, 27.5% from ScienceDirect, and 47.0% from Scopus, indicating that this study is supported by diverse and credible scientific sources.

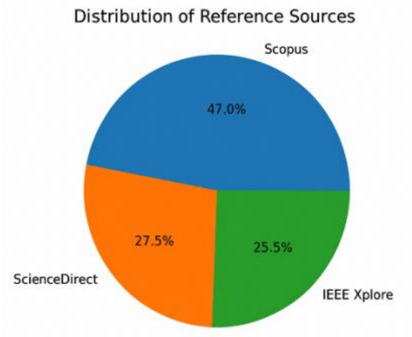

Figure 1: Distribution of Selected Literature by Data Source

3.2. Formulating the Research Question

To guide the analysis, research questions (RQ1–RQ10) were formulated based on the main themes identified in the literature review in order to focus the study on deep learning-based edge detection [20]. The mapping of these research questions is illustrated in Figure 2.

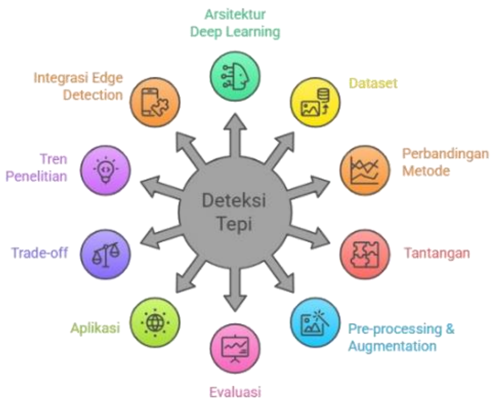

Figure 2: Mind Mapping Research Questions

- RQ1: What are the most widely used deep learning architectures (CNNs, Transformers, GANs) for edge detection over the past 5 years?
- RQ2: What are the standard datasets used to train and evaluate edge detection algorithms?
- RQ3: How do deep learning-based methods perform compared to traditional methods (such as Sobel or Canny)?
- RQ4: What are the main challenges (such as noise, computational cost, or crispness) still faced in edge detection today?
- RQ5: How does network architecture (e.g., U-Net, ResNet, Vision Transformer) affect the quality of edge detection?
- RQ6: How do pre-processing and augmentation techniques influence edge detection results?
- RQ7: What evaluation methods are most commonly used in edge detection?
- RQ8: What is the role of edge detection in real-world applications such as medical imaging or autonomous driving?
- RQ9: What is the trade-off between accuracy and computational efficiency in modern edge detection methods?
- RQ10: What are the future trends in AI-based edge detection research?

Finding the most popular deep learning architectures such as CNNs, Transformers, and GANs-for edge detection over the previous five years is the goal of the first research question (RQ1). This is important for understanding technological developments and the most effective approaches in this field. Furthermore, RQ2 focuses on identifying standard datasets commonly used in training and evaluating edge detection models, thereby determining the most relevant and frequently used data sources in research. In order to determine the advantages and disadvantages of each strategy, RQ3 compares the effectiveness of deep learning-based techniques with conventional techniques like

Sobel and Canny. RQ4 examines the major challenges still faced in edge detection, such as noise, high computational costs, and the sharpness of detection results (crispness). RQ5 focuses on analyzing the influence of network architectures, such as U-Net, ResNet, and Vision Transformer, on the quality of the resulting edge detection.

The objective of RQ6 is to evaluate the role of pre-processing techniques and data augmentation in improving the performance of edge detection models. In order to determine the assessment standards used, RQ7 seeks to identify the most popular evaluation techniques in edge detection research. In order to comprehend the impact of this technology on daily life, RQ8 explores the use of edge detection in a variety of real-world applications, including autonomous driving and medical imaging. RQ9 examines the trade-off between computing economy and accuracy in contemporary edge detection techniques, especially in light of resource limitations. Finally, RQ10 aims to identify future trends in AI-based edge detection research, including potential directions for technological development.

3.3. Data Validity and Literature Review

To ensure that the articles used are truly relevant to the subject of edge detection for picture segmentation using deep learning, the data eligibility and literature review stages of this study were conducted systematically in accordance with the PRISMA methodological flowchart [21].

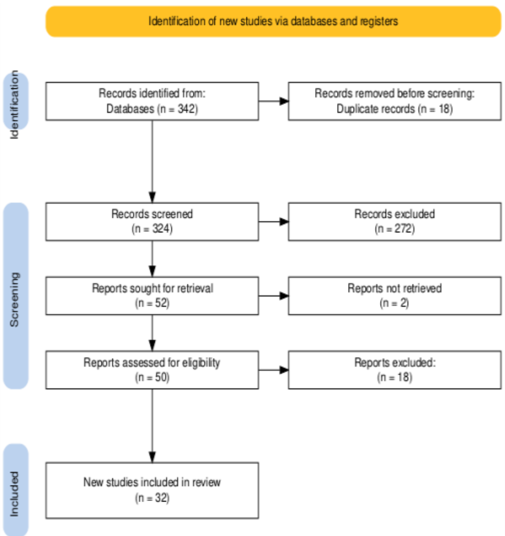

Figure 3: The research selection process utilized the PRISMA Flowchart, which consists of the Identification, Screening, and Inclusion stages

Based on the initial identification process, 342 papers in all were obtained from different scientific databases. 324 items were left for the screening phase after 18 duplicates were eliminated. At this stage, the papers' titles and abstracts were used for screening; 272 articles were excluded because they were not relevant to the research topic. Additionally, 52 articles were selected for full-text review, but two articles were inaccessible, leaving only 50 articles to be analyzed in the eligibility phase. The established inclusion and exclusion criteria were used to conduct further evaluation.

The inclusion criteria for this study were articles that discussed techniques for edge detection based on deep learning, focused on image segmentation, and were published in full text. On the other hand, articles that did not use a deep learning approach, were not relevant to image segmentation, had unclear methodologies, or were duplicates of previous research were excluded. The results of the eligibility screening indicated that 18 articles were excluded. Consequently, 32 articles were deemed eligible to serve as the basis for the literature analysis in this research.

Deep learning techniques are now the most widely used method for identifying image edges in segmentation, according to an examination of these 32 studies. Models including Convolutional Neural Networks (CNNs), U-Nets, and Fully Convolutional Networks (FCNs) have demonstrated superior accuracy in object boundary detection when compared to traditional methods [11][12].

Additionally, some research has created more sophisticated methods by fusing attention mechanisms with multi-scale feature extraction to enhance edge detection efficiency, especially in extremely complex images [15][31] like nature and medical images. The clarity of object boundaries has also been significantly improved by the combination of edge detection and semantic segmentation.

The literature review does, however, also highlight a number of issues that still need to be resolved, such as the requirement for a large number of labeled datasets, the high model complexity that affects computational requirements, and the challenge of identifying edges in images with low contrast or noise [17][19]. Overall, the study's conclusions show that deep learning for edge identification in picture segmentation has advanced significantly. The goal of current research is to create models that are lighter, more effective, and able to function in real time [32] without compromising accuracy.

4. A step before the final submission

This section provides a comprehensive summary of the models analyzed in this study, along with the key findings derived from the systematic literature review. The discussion is systematically organized to address each of the established research questions and is supported by the results of the analysis of 32 scientific articles selected through a rigorous screening process.
There are two primary elements to the discussion. The development is reviewed in the first section, advantages, and limitations of various categories of models used in deep learning-based edge detection based on the reviewed studies. The second section summarizes the findings to provide structured and comprehensive answers to each research question.

4.1 Summary of Edge Detection Models

Based on a survey of the literature, this section provides a thorough overview of advancements in deep learning-based edge detection models. Convolutional Neural Networks (CNNs), multi-scale models, encoder-decoder models, and hybrid approaches based on attention processes are examples of deep neural network architectures that are used to replace traditional methods [11][13].

In general, the development of edge detection models demonstrates improvements in accuracy, generalization ability, and the processing of more complex features [12][14]. Because CNN-based models can extract hierarchical characteristics from images, they are the main foundation [11][33]. Additionally, encoder-decoder architectures allow for more accurate reconstruction of spatial information, and multi-scale models were created to overcome problems in recording fluctuations in object size [13], [14]. In order to enhance overall performance, recent advancements have resulted in the integration of multiple approaches into hybrid models [34].

Each strategy has advantages and disadvantages, especially when it comes to detection accuracy, computational complexity, and training data requirements, according to a thorough analysis of these models [17][18]. This summary also reflects current research trends focused on improving edge detection quality under various image conditions, including images with high noise, low contrast, and complex objects [19]. Additionally, computational efficiency and real-time implementation capabilities are key considerations in model development [10][17].

Table 1. summarizes the categories of edge detection models, their main advantages, limitations, and relevant research references to provide a more systematic overview.

Model	Example Model / Paper	Advantages	Keterbatasan	Sumber Data
CNN-based Models	Crisp Edge Detection (PiDiNet + Canny refinement), DoG / DoqG	Mampu menangkap fitur lokal dengan baik, performa stabil untuk edge detection dasar, meningkatkan ketajaman edge	Sensitif terhadap kualitas label, sulit menangkap konteks global	Zhang *et al.*, 2023), (Li *et al.*, 2024)
Encoder-Decoder Models	EDC-UNet, EEU-Net, AttEUnet, Crop Segmentation UNet	Struktur kuat untuk segmentasi, mampu menggabungkan fitur low-level & high-level, akurasi tinggi	Membutuhkan data besar, komputasi tinggi	(Zhou *et al.*, 2025), (Khan *et al.*, 2024), (Wang *et al.*, 2024), (Liu *et al.*, 2022)
Multi-scale & Attention-based Models	Abel-Net, ELU-Net, WETS-Net, EGFF-Net	Mampu menangkap fitur multi-skala, attention meningkatkan fokus edge	Arsitektur kompleks, training sulit	(Chen *et al.*, 2025), (Sun *et al.*, 2024), (Zhao *et al.*, 2024), (Li *et al.*, 2024)
Transformer-based Models	EE-FPS-SwinUNet, EE-TransUNet, PSM-FFEG	Menangkap long-range dependency, cocok untuk citra kompleks	Komputasi sangat tinggi	(Zhang *et al.*, 2025), (Wang *et al.*, 2024), (Liu *et al.*, 2025)
Hybrid / Integrated Models	UMIAD-EGMF, EGSDK-Net, Mask Guidance Pyramid Network	Kombinasi edge + segmentasi → hasil boundary lebih presis	Desain rumit, sulit implementasi	(Yang *et al.*, 2026), (Zhou *et al.*, 2025), (Li *et al.*, 2023)

4.2 Summary of Findings Based on the Research Questions

The results from a few chosen research are summarized in this section as part of the Systematic Literature Review (SLR) procedure [20]. The analysis is predicated on a thorough assessment of current studies on edge detection for picture segmentation using deep learning, focusing on the development of model architectures, the use of datasets, performance comparisons, and their implementation across various application domains.

The objective of this subsection is to systematically address the research questions (RQ1–RQ10) by identifying patterns, trends, and research gaps present in the literature. Each answer is formulated by summarizing the methods used, their effectiveness in improving edge detection quality, and the limitations still encountered, particularly in the domains of medical imaging and complex visual environments.

This part also offers a critical evaluation of the contributions of the most recent methods, like attention mechanisms, multiscale feature extraction, and transformer-based architectures to improving boundary precision and segmentation accuracy. On the other hand, major challenges such as computational complexity, edge crispness issues, and data limitations are also discussed as factors influencing the development of more robust edge detection models. Overall, the findings in this subsection not only describe the state of the art at the moment while also offering a path for further study in the area of AI-based edge detection.

RQ 1: The Convolutional Neural Network (CNN)-based model is the most popular architecture in edge detection, according to the findings of the literature review, particularly encoder–decoder approaches such as U-Net and its various variants [35]. This dominance is attributed to the ability of CNNs to effectively extract spatial features, especially for local details in images [12]. Additionally, recent developments show an increasing use of Transformer-based models, such as Swin Transformer, which are capable of capturing global dependencies and broader context [18]. Hybrid models that combine CNNs and Transformers are also becoming widely used because they can integrate the strengths of both [23]. Meanwhile, the use of Generative Adversarial Networks (GANs) tends to be limited and is more frequently utilized for data augmentation or image quality enhancement. Figure X shows a comparison of deep learning architectures used in edge detection, including CNNs, U-Net, Transformers, and hybrid models.

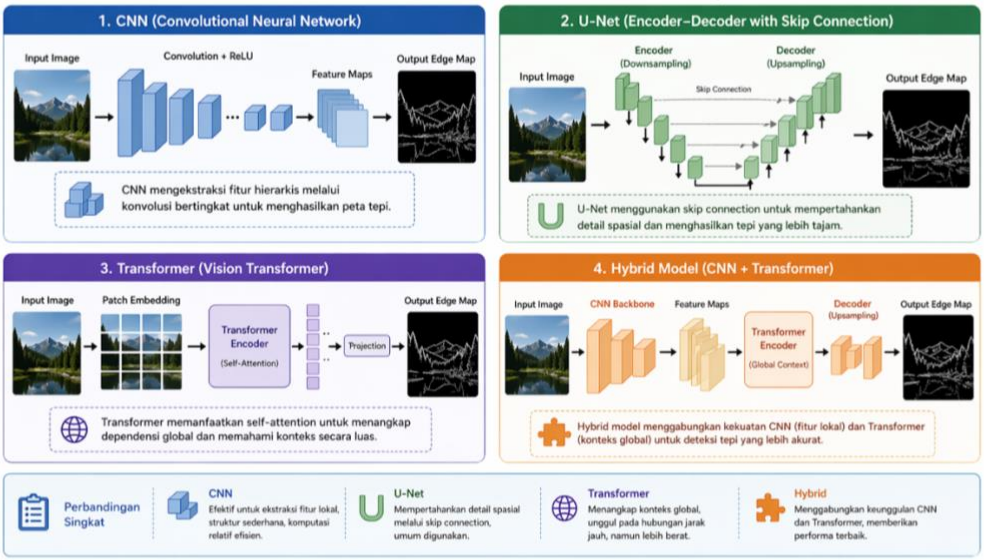

Figure 4: A comparison of deep learning architectures for edge detection, including CNNs, U-Nets, Transformers, and hybrid models.

RQ 2: Datasets used in edge detection research generally come from two main domains: medical images and general images (computer vision) [9][11]. Medical datasets such as LIDC-IDRI, LUNA16, ISIC 2018, as well as various MRI and CT scan datasets, are widely used due to the need for precise segmentation of object boundaries [12][14]. Meanwhile, general datasets such as Cityscapes and MS COCO are used for more complex scenarios like urban environments [10][23]. However, most studies face challenges such as data imbalance and limitations in accurate annotations, particularly in medical datasets [18].

RQ 3: When it comes to accuracy and the capacity to comprehend intricate visual contexts, deep learning-based techniques typically outperform more conventional techniques like Sobel and Canny [5][11]. Improvements in assessment metrics like the Dice coefficient and Intersection over Union (IoU) [12][14]. demonstrate this. Nonetheless, classical approaches continue to be useful for resource-constrained applications due to their advantages in terms of computing efficiency and simplicity of implementation [5][6], comparison of edge detection outcomes, accuracy measures, and computing speed between deep learning and conventional approaches is presented in Figure 5.

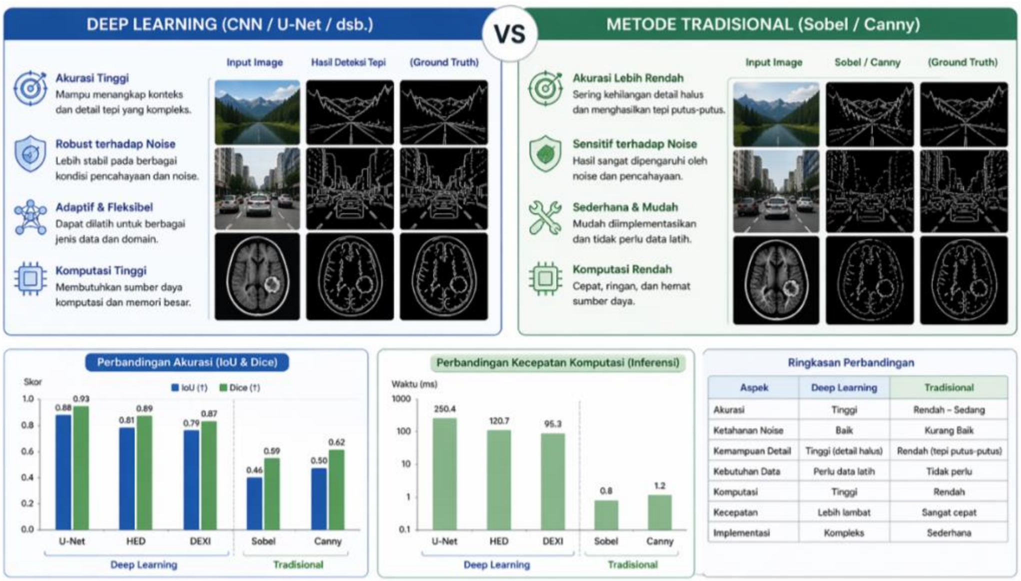

Figure 5: A Comparison of the Performance of Deep Learning Methods and Traditional Methods

RQ 4: Despite significant progress, deep learning-based edge detection still faces several major challenges [16]. One of these is the issue of noise and label quality, which can result in edge detection results that lack sharpness (crispness issue) [18]. Additionally, blurred object boundaries in complex images also pose a challenge [19]. Other challenges include high computational costs, particularly in Transformer-based models [17], as well as difficulties in handling objects with diverse scale variations (the multi-scale problem).

RQ 5: Network architecture has a significant influence on edge detection quality [14]. U-Net-based and encoder–decoder models have proven effective in preserving spatial details [13]. The use of backbones such as ResNet can improve feature extraction quality [23], while Vision Transformers offer advantages in understanding global context [17]. Furthermore, the integration of additional modules such as attention mechanisms and edge-aware modules has proven capable of enhancing object boundary sharpness and overall segmentation accuracy.

RQ6: The quality of edge detection results is greatly enhanced by preprocessing and data augmentation techniques. Before the input is fed into the model, preprocessing techniques including normalization, denoising, and grayscale conversion assist reduce noise and make edge structures more visible [7]. However, by increasing the variety of training data, data augmentation techniques like rotation, flipping, scaling, and lighting adjustments might strengthen the model's resistance to real-world circumstances [12][16]. It has been demonstrated that combining the two enhances the model's capacity for generalization, lessens overfitting, and results in more accurate and reliable edge detection under a range of visual situations. The workflow from picture input to the pre-processing and augmentation phases to the final edge detection output is shown in Figure 7.

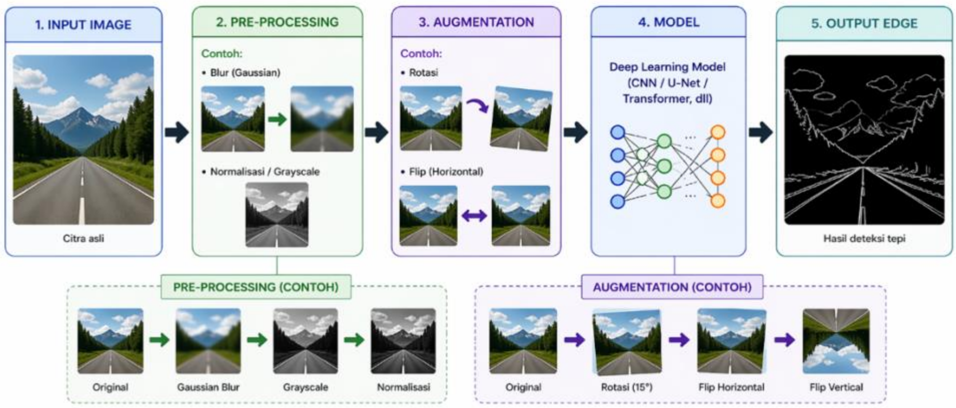

Figure 6: A pipeline for preprocessing, data augmentation, and edge detection using deep learning models.

RQ7: In edge detection, the most commonly used evaluation methods are metrics based on comparisons between predicted results and ground truth. Some key metrics include Precision, Recall, and F1-score, which measure the balance between correct edge detections and false detections [12]. Additionally, specialized metrics such as Average Precision (AP), Optimal Data Set Scale (ODS), and Optimal Image Scale (OIS) are also used [1][36], particularly on standard datasets like BSDS500. These metrics provide a comprehensive overview of model performance, both in terms of detection accuracy and consistency across various image scales.

RQ8: Edge detection plays a crucial role in various real-world applications, particularly in medical imaging and autonomous driving [10]. In medical imaging, edge detection is used to identify the boundaries of organs, tissues, or lesions, thereby aiding in the diagnosis of diseases such as tumors or structural abnormalities [31]. Meanwhile, in autonomous driving, edge detection serves to recognize road boundaries, markings, vehicle objects, and pedestrians [23], which form the basis for navigation system decision-making. The safety and dependability of the system are directly impacted by edge detection accuracy, which is why deep learning-based techniques are being used more frequently to improve precision in challenging situations. Figure 8 illustrates the application of edge detection in the domains of medical imaging and autonomous driving.

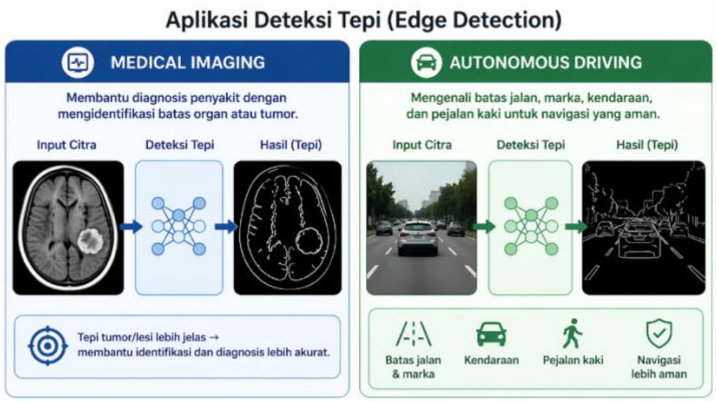

Figure 7: The Application of Edge Detection in Medical Imaging and Autonomous Driving

RQ9: Accuracy and computing efficiency are significantly traded off in contemporary edge detection techniques. Because they can capture more intricate information, models with complicated structures, like deep CNNs or Transformers, typically achieve high accuracy [17], but they require substantial computational resources and longer inference times [16]. Conversely, lighter and more efficient models, such as lightweight CNNs or models based on pruning and quantization, offer higher speed and lower memory consumption [32], but often suffer from reduced accuracy. Therefore, model selection is typically tailored to the application's needs, prioritizing either speed (real-time) or accuracy of results.

RQ10: Future trends in AI-based edge detection research indicate a shift toward more efficient, adaptive, and context-aware models. Because Transformers and hybrid models (CNN-Transformers) can capture global relationships in images, their application is growing [17]. To overcome the drawbacks of labeled data, research is now concentrating on self-supervised and semi-supervised learning. Another important area of focus is integration with edge computing technology, which allows models to operate in real-time on resource-constrained devices [16]. On the other hand, improving model interpretability and applications in specific domains such as healthcare and smart cities remain areas of ongoing development

5. Conclusion

An extensive assessment of the literature on the advancement of deep learning-based edge detection techniques for image segmentation is presented in this work. Convolutional Neural Networks (CNNs), U-Nets, and Transformers deep learning-based techniques that can increase edge detection accuracy have replaced traditional methods, according to an examination of 32 publications. It has also been demonstrated that combining attention processes with multi-scale feature extraction enhances the quality of object boundaries. There are still issues, though, such the requirement for a lot of labeled data, computational cost, and restrictions on model generalization. In order to create models that are more effective, flexible, and able to function in real-time across a variety of application domains, more research is advised.

Furthermore, the results of the study show that improvements in deep learning technology have significantly improved the performance of picture segmentation systems in a variety of domains, including digital security, autonomous vehicles, remote sensing, and medicine. Techniques like data augmentation, transfer learning, and lightweight models are also being used more frequently to overcome computing resource constraints and dataset size constraints. Deep learning-based edge detection techniques should continue to improve in terms of accuracy, efficiency, and adaptability with the ongoing development of artificial intelligence technology and contemporary computing hardware. This will contribute more broadly to the future development of intelligent image processing systems.

References

[1] B. Tian and W. Wei, "Research Overview on Edge Detection Algorithms Based on Deep Learning and Image Fusion," *Secur. Commun. Networks*, vol. 2022, no. 1, 2022, doi: 10.1155/2022/1155814.

[2] Y. Wu and Q. Li, "The Algorithm of Watershed Color Image Segmentation Based on Morphological Gradient," *Sensors*, vol. 22, no. 21, 2022, doi: 10.3390/s22218202.

[3] X. Wang, L. Shu, R. Han, F. Yang, T. Gordon, and X. Wang, "A Survey of Farmland Boundary Extraction Technology Based on Remote Sensing Images," 2023, doi: 10.3390/electronics12051156.

[4] M. Mushtaq, M. U. Akram, N. S. Alghamdi, J. Fatima, and R. F. Masood, "Localization and Edge-Based Segmentation of Lumbar Spine Learning Models," 2022, doi: 10.3390/s22041547.

[5] R. A. A S and S. Gopalan, "Comparative Analysis of Eight Direction Sobel Edge Detection Algorithm for Brain Tumor MRI Images," *Procedia Comput. Sci.*, vol. 201, no. C, pp. 487–494, 2022, doi: 10.1016/j.procs.2022.03.063.

[6] J. Agustín Tortolero Osuna and A. Jorge Rosales Silva, "Parallel Peer Group Filter for Impulse Denoising in Digital Images on Gpu," *Comput. Informatics*, vol. 38, pp. 1320–1340, 2019, doi: 10.31577/cai.

[7] S. P. Pathak and S. A. Patil, "Evaluation of Effect of Pre-Processing Techniques in Solar Panel Fault Detection," *IEEE Access*, vol. 11, no. July, pp. 72848–72860, 2023, doi: 10.1109/ACCESS.2023.3293756.

[8] J. C. Avendaño, J. Leander, and R. Karoumi, "Image-Based Concrete Crack Detection Method Using the Median Absolute Deviation," *Sensors*, vol. 24, no. 9, 2024, doi: 10.3390/s24092736.

[9] H. Fang *et al.*, "ADAM Challenge: Detecting Age-Related Macular Degeneration From Fundus Images," *IEEE Trans. Med. Imaging*, vol. 41, no. 10, pp. 2828–2847, 2022, doi: 10.1109/TMI.2022.3172773.

[10] Q. Cheng, H. Wang, B. Zhu, Y. Shi, and B. Xie, "A Real-Time UAV Target Detection Algorithm Based on Edge Computing," *Drones*, vol. 7, no. 2, 2023, doi: 10.3390/drones7020095.

[11] L. Xiao, B. Zhou, and C. Fan, "Automatic brain MRI tumors segmentation based on deep fusion of weak edge and context features," *Artif. Intell. Rev.*, vol. 58, no. 5, 2025, doi: 10.1007/s10462-025-11151-8.

[12] S. Umirzakova, S. Ahmad, S. Mardieva, S. Muksimova, and T. K. Whangbo, "Deep learning-driven diagnosis: A multi-task approach for segmenting stroke and Bell's palsy," *Pattern Recognit.*, vol. 144, no. July, p. 109866, 2023, doi: 10.1016/j.patcog.2023.109866.

[13] J. Chen *et al.*, "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation," pp. 1–13, 2021, doi: 10.48550/arXiv.2102.04306.

[14] L. Tong *et al.*, "LiViT-Net: A U-Net-like, lightweight Transformer network for retinal vessel segmentation," *Comput. Struct. Biotechnol. J.*, vol. 24, no. February, pp. 213–224, 2024, doi: 10.1016/j.csbj.2024.03.003.

[15] Y. Yin, Y. Guo, L. Deng, and B. Chai, "Improved PSPNet-based water shoreline detection in complex inland river scenarios," *Complex Intell. Syst.*, vol. 9, no. 1, pp. 233–245, 2023, doi: 10.1007/s40747-022-00793-8.

[16] M. Jahanbakht, W. Xiang, N. J. Waltham, and M. R. Azghadi, "Distributed Deep Learning and Energy-Efficient Real-Time Image Processing at the Edge for Fish Segmentation in Underwater Videos," *IEEE Access*, vol. 10, no. July, pp. 117796–117807, 2022, doi: 10.1109/ACCESS.2022.3202975.

[17] A. Dosovitskiy *et al.*, "an Image Is Worth 16X16 Words: Transformers for Image Recognition At Scale," *ICLR 2021 - 9th Int. Conf. Learn. Represent.*, 2021.

[18] J. Liu *et al.*, "Local Label Point Correction for Edge Detection of Overlapping Cervical Cells," *Front. Neuroinform.*, vol. 16, no. May, pp. 1–14, 2022, doi: 10.3389/fninf.2022.895290.

[19] S. Yang, B. Ni, W. Du, and T. Yu, "Research on an Improved Segmentation Recognition Algorithm of Overlapping Agaricus bisporus," *Sensors*, vol. 22, no. 10, 2022, doi: 10.3390/s22103946.

[20] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," Mar. 29, 2021, *BMJ Publishing Group*. doi: 10.1136/bmj.n71.

[21] N. R. Haddaway, M. J. Page, C. C. Pritchard, and L. A. McGuinness, "PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis," *Campbell Syst. Rev.*, vol. 18, no. 2, pp. 1–12, 2022, doi: 10.1002/cl2.1230.

[22] F. Yuanbin, Guoxiaojie, H. Qiming, L. Di, M. Jiayi, and L. Haibin, "Hierarchical Image Peeling: A Flexible Scale-space Filtering Framework," 2021, [Online]. Available: http://arxiv.org/abs/2104.01534

[23] H. Zhang, F. Shao, X. He, Z. Zhang, Y. Cai, and S. Bi, "Research on Object Detection and Recognition Method for UAV Aerial Images Based on Improved YOLOv5," *Drones*, vol. 7, no. 6, 2023, doi: 10.3390/drones7060402.

[24] M. Mubashar, N. Khan, A. R. Sajid, M. H. Javed, and N. U. Hassan, “Have We Solved Edge Detection? A Review of State-of-the-Art Datasets and DNN Based Techniques,” *IEEE Access*, vol. 10, no. July, pp. 70541–70552, 2022, doi: 10.1109/ACCESS.2022.3187838.

[25] S. Ben Chaabane and A. Bushnag, “Color Edge Detection Using Multidirectional Sobel Filter and Fuzzy Fusion,” *Comput. Mater. Contin.*, vol. 74, no. 2, pp. 2839–2852, 2023, doi: 10.32604/cmc.2023.032760.

[26] M. Hagara, R. Stojanović, A. Šatka, P. Kubinec, and O. Ondráček, “Modified algorithm of unimodal thresholding for FPGA implementation,” *Microprocess. Microsyst.*, vol. 94, no. February, pp. 4–10, 2022, doi: 10.1016/j.micpro.2022.104669.

[27] N. U. Rehman *et al.*, “Edge of discovery: Enhancing breast tumor MRI analysis with boundary-driven deep learning,” *Biomed. Signal Process. Control*, vol. 95, no. PA, p. 106291, 2024, doi: 10.1016/j.bspc.2024.106291.

[28] B. Liu, H. Zhu, and W. Zhang, “EDC-UNet: A Pulmonary Nodule Segmentation Method Based on Edge Detail Enhancement.”

[29] L. Zhu, Y. Cai, J. Liao, and F. Wu, “Lung Parenchyma Segmentation Based on U-Net Fused With Shape Stream,” *IEEE Access*, vol. 12, no. January, pp. 29238–29251, 2024, doi: 10.1109/ACCESS.2024.3365577.

[30] B. Cheng, M. Tian, S. Jiang, W. Liu, and Y. Pang, “Multi-Task Learning and Multimodal Fusion for Road Segmentation,” *IEEE Access*, vol. 11, no. February 2022, pp. 18947–18959, 2023, doi: 10.1109/ACCESS.2022.3151372.

[31] X. Fang, E. Zhang, B. Li, and B. Zhai, “A Fast and High-Precision Ellipse Detection Method Based on the Candy’s Theorem,” *IEEE Access*, vol. 11, no. September, pp. 102971–102980, 2023, doi: 10.1109/ACCESS.2023.3315848.

[32] L. Ma, J. Han, C. Dong, T. Fang, W. Liu, and X. He, “Conveyor Belt Deviation Detection for Mineral Mining Applications Based on Attention Mechanism and Boundary Constraints,” *Sensors*, vol. 25, no. 22, pp. 1–29, 2025, doi: 10.3390/s25226945.

[33] M. Tabb and N. Ahuja, “Multiscale image segmentation by integrated edge and region detection,” *IEEE Trans. Image Process.*, vol. 6, no. 5, pp. 642–655, 1997, doi: 10.1109/83.568922.

[34] T. An, W. Huang, D. Xu, Q. He, J. Hu, and Y. Lou, “A Deep Learning Framework for Boundary-Aware Semantic Segmentation,” *2025 5th Int. Conf. Artif. Intell. Ind. Technol. Appl. AIITA 2025*, pp. 886–890, 2025, doi: 10.1109/AIITA65135.2025.11048045.

[35] N. Ofir and Y. Keller, “Multi-scale processing of noisy images using edge preservation losses,” *Proc. - Int. Conf. Pattern Recognit.*, pp. 8751–8758, 2020, doi: 10.1109/ICPR48806.2021.9413325.

[36] X. Ru, Y. Wang, L. Peng, and J. Li, “An Adaptive Extraction Method for Knitted Patterns Based on Bayesian-Optimized Bilateral Filtering,” *Appl. Sci.*, vol. 16, no. 5, pp. 1–24, 2026, doi: 10.3390/app16052526.