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Robustness Comparison of Traditional and Deep Learning-Based Image Segmentation Models on Noisy Images

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***Abstract*— Detecting objects in images with precision becomes increasingly difficult when the input is degraded by noise or distortion, as is common in real-world applications. This study investigates and compares the performance of a traditional edge detection technique (Canny) and a deep learning-based model (U- Net) for binary image segmentation under noisy conditions. We simulate three types of image noise—Gaussian, Salt & Pepper, and Motion Blur—on a public dataset and evaluate both models using Dice Score, Intersection over Union (IoU), and Structural Similarity Index (SSIM) to assess their quantitative accuracy and perceptual consistency. While U-Net demonstrates stronger resilience in capturing complex structures and maintaining segmentation accuracy, Canny proves more computationally efficient and surprisingly stable under certain distortions. Our results highlight the importance of selecting segmentation methods based not only on accuracy but also on noise robustness and deployment constraints. This work offers practical insights into the trade-offs between traditional and deep learning models for vision tasks in noisy environments.**
Keywords— Image Segmentation, U-Net, Canny Edge Detection, Noise Robustness, Dice Score, IoU, SSIM, Deep Learning, Computer Vision

1. INTRODUCTION

Image segmentation plays a vital role in computer vision, enabling the precise delineation of objects within an image, which is essential for downstream tasks such as object recognition, medical diagnosis, and autonomous navigation. While numerous models have been developed to perform segmentation with high accuracy under ideal conditions, real-world scenarios often involve noisy or degraded images due to environmental factors like motion blur, low lighting, or sensor interference. This degradation complicates segmentation by obscuring object boundaries and introducing irregular patterns, thereby testing a model's robustness and generalization capabilities. Traditional image segmentation methods such as Canny edge detection are appreciated for their simplicity, computational efficiency, and ability to extract prominent edges. However, their performance tends to degrade under noisy conditions, especially when object boundaries are distorted or unclear. In contrast, deep learning- based models like U-Net have advanced the field significantly by leveraging convolutional architectures that learn hierarchical features from data. U-Net, in particular, is well-known for its ability to perform semantic segmentation with high spatial accuracy, even when trained on relatively small datasets. Its encoder-decoder structure with skip connections enables it to capture both low-level and high-level features, making it a promising candidate for noise-resilient segmentation. This research presents a comparative analysis of a traditional edge detection method (Canny) and a deep learning segmentation model (U-Net) when applied to images affected by three distinct types of noise: Gaussian, Salt & Pepper, and Motion Blur. The objective is to evaluate how well each approach handles noise while maintaining segmentation quality. To do this, we employ a widely used annotated dataset and assess model performance using quantitative metrics such as Dice Score and Intersection over Union (IoU), along with the Structural Similarity Index (SSIM) to measure visual consistency. The results aim to provide meaningful insights into the strengths and limitations of each approach, offering guidance for selecting appropriate segmentation techniques in practical, noise- affected scenarios.

2. RELATED WORK

Image segmentation has been widely explored through traditional methods like edge detection, with Canny being a popular choice for its efficiency. However, such methods often struggle in noisy or degraded conditions where edge clarity is reduced. In contrast, deep learning models like U-Net have shown superior performance by learning spatial hierarchies and preserving fine details through their encoder-decoder structures. U-Net has been particularly effective in medical and semantic segmentation tasks, demonstrating robustness even with limited data. Recent studies, such as those by Yu et al., emphasize that deep models outperform classical ones in handling noise and complex visual patterns. Building on this, our study compares Canny and U-Net under noisy image conditions, assessing their segmentation quality using both quantitative metrics and perceptual evaluations.

3. METHODOLOGY

This study adopts a systematic approach to evaluate and compare the performance of a traditional and a deep learning model in image segmentation under noisy conditions. The methodology is structured as follows:

I – Dataset Preparation: The Oxford-IIIT Pet Dataset, which contains images of various pet breeds along with pixel-wise segmentation masks, is used for this study. A subset of 50 images is selected and resized to 128×128 pixels for computational efficiency and consistency in evaluation.

II - Noise Injection: To simulate real-world distortions, each image in the test set is modified using three common types of noise:

- Gaussian Noise: Simulates sensor noise.
- Salt & Pepper Noise: Mimics random bit errors.
- Motion Blur: Emulates camera shake or fast movement.

III - Model Selection: Two segmentation models are selected for performance comparison:

- **Canny Edge Detection:** A classical edge-based method used for identifying object boundaries.
- **U-Net:** A deep learning model with an encoder-decoder architecture designed for semantic segmentation, known for its performance on medical and natural image datasets.

IV -Model Training and interface: The U-Net model is trained on 80% of the dataset using binary segmentation masks, while 20% is reserved for testing. The Canny model, being rule-based, is applied directly to noisy images without training. Both models generate segmentation outputs on the same set of noisy test images.

V – Performance Evaluation:
The output masks from both models are evaluated using:

- Dice Score: Measures the overlap between predicted and true masks.
- Intersection over Union (IoU): Evaluates the accuracy of predicted segmentation regions.
- Structural Similarity Index (SSIM): Assesses the perceptual similarity between the segmented result and the ground truth.

VI – Model Comparison:
The performance metrics for each model across all noise types are compared to assess robustness, accuracy, and visual fidelity. This analysis highlights the trade-offs between traditional and deep learning approaches in real-world segmentation tasks.

4. ABOUT THE MODEL

This research investigates the effectiveness of two distinct models, U- Net and Canny Edge Detection, in performing image segmentation under noisy conditions.

U-Net is a deep learning-based model designed specifically for semantic segmentation tasks. Its architecture follows an encoder- decoder structure, where the encoder compresses spatial information into feature representations, and the decoder reconstructs detailed segmentation maps. A key strength of U-Net lies in its skip connections, which directly link corresponding layers in the encoder and decoder, preserving fine-grained spatial features. This design allows U-Net to achieve high accuracy even with relatively small training datasets, making it highly adaptable to a variety of segmentation problems, including medical imaging and object localization. U-Net's ability to learn hierarchical representations and contextual relationships makes it particularly resilient against image distortions such as noise and blur, which commonly degrade segmentation quality. Conversely, Canny Edge Detection is a traditional, rule-based method that identifies object boundaries by detecting sharp intensity gradients in an image. The technique involves a series of steps, including noise reduction, gradient calculation, non-maximum suppression, and edge tracking, to accurately delineate edges. While Canny is computationally lightweight and does not require any training, it primarily focuses on local pixel information and lacks an understanding of broader image context. As a result, its performance can be sensitive to noise and image artifacts. However, due to its simplicity, speed, and interpretability, Canny remains a widely used baseline for segmentation tasks, particularly in resource-constrained environments.

This study compares U-Net's advanced feature learning capabilities with Canny's efficiency and simplicity to analyze their respective strengths and limitations when segmenting noisy images. Through this comparison, we aim to offer a nuanced understanding of how traditional and deep learning approaches respond to real-world image degradations.

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5. NOISE TECHNIQUES

Noise simulation is an essential aspect of image processing research, particularly for evaluating the robustness and reliability of segmentation models. In real-world scenarios, images often contain various imperfections introduced by environmental factors, sensor limitations, or transmission errors. In this study, we deliberately introduce three types of noise—Gaussian noise, Salt & Pepper noise, and Motion Blur—to the dataset. This allows us to examine how well traditional and deep learning models perform when faced with noisy, distorted inputs, providing insights into their real-world applicability.

1. Gaussian Noise

Gaussian noise is a statistical noise characterized by a normal distribution of pixel intensity values around the true value. It is often encountered in images captured under low-light conditions or through imperfect camera sensors. The primary reason for introducing Gaussian noise in this study is to simulate the subtle, random variations that real-world imaging devices frequently introduce.
For image segmentation tasks, the presence of Gaussian noise can obscure object boundaries and create small, scattered intensity fluctuations across the image. This can significantly challenge edge-based methods like Canny, which rely on detecting sharp gradients. Conversely, deep learning models like U-Net, which learn hierarchical and contextual representations, are expected to better manage such distortions. Evaluating model performance under Gaussian noise helps reveal their resilience to common sensor imperfections, a crucial factor for deploying segmentation models in fields like medical imaging and surveillance.

2. Salt and Pepper Noise

Salt & Pepper noise, also known as impulse noise, randomly replaces pixel values with either the maximum or minimum value, causing scattered white and black dots across an image. It typically arises from transmission errors, faulty memory locations, or sudden disturbances during image acquisition.
In segmentation tasks, Salt & Pepper noise presents a serious challenge by introducing abrupt, high-contrast artifacts that can be mistaken for edges or object boundaries. Traditional methods like Canny are particularly vulnerable to such noise, often resulting in false edges and fragmented segmentations. By applying Salt & Pepper noise, this study assesses the models' ability to distinguish true object boundaries from random high-contrast noise. Testing under such conditions offers valuable insights into the robustness of segmentation models in harsh operational environments, such as real-time communications or remote sensing systems.

3. Motion Blur

Motion blur occurs when either the camera or the object being captured moves during the exposure time, causing a smearing effect across the image. This type of noise simulates real-world challenges in dynamic settings like vehicle-mounted cameras, handheld devices, or fast-moving subjects .In the context of image segmentation, motion blur can significantly degrade boundary clarity, stretching edges and blending adjacent regions together. Traditional edge detection methods often fail in blurred images, producing incomplete or inaccurate segmentations. Deep learning models, however, may leverage contextual cues to reconstruct missing or distorted information. By introducing motion blur into the dataset, this study evaluates how effectively each model can handle motion-induced distortions and maintain segmentation quality.

In summary, The deliberate application of Gaussian noise, Salt & Pepper noise, and Motion Blur provides a comprehensive framework for evaluating the robustness of segmentation models under different real-world imperfections. Gaussian noise tests resilience to random fluctuations; Salt & Pepper noise challenges the models with sharp, isolated disturbances; and Motion Blur examines their ability to cope with

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spatial distortions due to movement. By simulating these noise conditions, the study aims to provide a realistic and thorough assessment of traditional and deep learning-based segmentation techniques, highlighting their strengths and limitations when deployed outside controlled laboratory settings.

6. COMPARATIVE ANALYSIS OF TRADITIONAL AND DEEP LEARNING MODELS ON GAUSSIAN NOISE-AFFECTED DATASET

This section evaluates the segmentation performance of the traditional Canny Edge Detection method and the U-Net deep learning model when applied to images affected by Gaussian noise. The models are compared using key metrics — Dice Score, Intersection over Union (IoU), and Structural Similarity Index (SSIM) — to determine their effectiveness in handling noise-distorted inputs. The dataset underwent Gaussian noise augmentation as part of the experimental setup, creating a challenging environment that tests the robustness and adaptability of both models. After noise application, both models generated segmentation masks, and their outputs were quantitatively and visually assessed.

Disc Score Analysis

Canny Edge Detection (Traditional Model) - The Canny model achieved a Dice Score of **0.171**. This relatively low value indicates that while the traditional model was able to detect some edges within the noisy images, it struggled significantly to capture the complete structure of the objects. The random fluctuations introduced by Gaussian noise likely disrupted the gradient calculations critical to Canny's operation, leading to fragmented or incomplete segmentations.

U-Net (Deep Learning Model) - In stark contrast, the U-Net model achieved a Dice Score of **1.0**, suggesting perfect overlap between the predicted segmentation masks and the ground truth. This result highlights U-Net’s exceptional capacity to learn robust features and maintain segmentation accuracy even when input quality is degraded. Its encoder-decoder architecture, combined with skip connections, allows it to preserve contextual and structural information that Gaussian noise alone cannot distort easily.

Intersection over Union Analysis

Canny Edge Detection - The IoU score for Canny was **0.093**, further reinforcing the model's difficulty in accurately segmenting noisy images. An IoU value this low indicates minimal intersection between the predicted and true masks, suggesting that Canny's reliance on sharp gradient changes makes it highly vulnerable to noise-induced distortions.

U-Net - The U-Net model also recorded an IoU score of **1.0**, indicating complete agreement with the ground truth masks. This reinforces the Dice Score results and demonstrates U-Net’s robustness in segmenting images with additive Gaussian noise.

Structural Similarity Index (SSIM) Analysis

Canny Edge Detection - The SSIM value for the traditional method was **0.018**, showing very low perceptual similarity between the segmented output and the ground truth. This is consistent with the fragmented edges produced by Canny under noisy conditions.

U-Net - The U-Net model achieved a slightly higher SSIM score of **0.024.** Although this value is also relatively low compared to typical SSIM scores, it reflects the fact that Gaussian noise affects overall visual quality. However, since segmentation focuses primarily on mask accuracy rather than photorealistic output, the perfect Dice and IoU scores suggest that U-Net successfully preserved object boundaries despite the noise.

When analyzing the performance of both models under Gaussian noise, it is evident that the U-Net deep learning model vastly outperforms the traditional Canny Edge Detection method across all evaluation metrics. The Dice and IoU scores indicate U-Net’s near- perfect segmentation ability, while the slight improvement in SSIM also shows better perceptual fidelity. In contrast, the Canny model failed to adapt to the random pixel-level intensity changes introduced by Gaussian noise, resulting in poor segmentation performance. These results underline the fundamental advantage of deep learning models in noisy environments: their capacity to learn global and local features enables them to be resilient to input distortions. Meanwhile, traditional models, which depend heavily on pixel-level gradient information, exhibit significant limitations under similar conditions. This analysis emphasizes the importance of model selection based on deployment conditions. For real-world scenarios where image degradation is common, deep learning-based approaches like U-Net are evidently more reliable and capable of maintaining segmentation quality.

7. COMPARATIVE ANALYSIS OF TRADITIONAL AND DEEP LEARNING MODELS ON SALT & PEPPER NOISE-AFFECTED DATASET

This section compares the performance of the traditional Canny Edge Detection method and the deep learning-based U-Net model on images affected by Salt & Pepper noise. Both models are evaluated using Dice Score, Intersection over Union (IoU), and Structural Similarity Index (SSIM) to assess segmentation accuracy and visual consistency under high-contrast, impulse noise conditions. This analysis helps reveal the strengths and weaknesses of each model when handling sharp, isolated distortions common in real-world imaging scenarios.

Dice Score Analysis

Canny Edge Detection (Traditional Model) - The traditional Canny model achieved a Dice Score of **0.392** on Salt & Pepper noise- distorted images. While this is an improvement compared to its performance under Gaussian noise, the score still indicates considerable segmentation errors. The scattered white and black pixels introduced by Salt & Pepper noise create artificial gradients that often mislead edge detectors, resulting in numerous false edges and fragmented segmentation maps.

U-Net (Deep Learning Model) - U-Net once again achieved a Dice Score of **1.0**, indicating perfect overlap between the predicted masks and ground truth. Despite the presence of sharp, high-contrast noise, U-Net effectively learned to differentiate true object boundaries from random impulse noise. This showcases the model's ability to generalize spatial patterns and structural features, even when local pixel values are heavily corrupted.

Intersection over Union (IoU) Analysis

Canny Edge Detection - The IoU score for the Canny method was **0.243**, reflecting modest overlap with the ground truth masks.

Although higher than its IoU performance on Gaussian noise, this score remains relatively low. The result demonstrates that while Canny could detect some true edges, it frequently misinterpreted noise artifacts as object boundaries, thereby reducing overall segmentation accuracy.

U-Net - U-Net maintained an IoU score of **1.0** even in the presence of Salt & Pepper noise. This result reaffirms the Dice Score findings and highlights U-Net's superior ability to maintain consistent and accurate segmentation despite severe noise interference.

Structural Similarity Index (SSIM) Analysis

Canny Edge Detection - The SSIM score for the traditional model was extremely low at **0.005**, indicating almost no perceptual similarity between the predicted segmentation and the ground truth. This severe degradation is expected, given that Salt & Pepper noise severely disrupts the image structure and Canny's reliance on pixel intensity gradients.

U-Net - The U-Net model achieved an SSIM score of 0.087, significantly higher than Canny's output but still relatively low compared to noise-free conditions. Although SSIM values are affected by the overall noise corrupting the image appearance, the perfect Dice and IoU scores suggest that U-Net successfully preserved the essential object structures needed for accurate segmentation.

The performance comparison under Salt & Pepper noise further highlights the robustness of deep learning models over traditional methods. While the Canny Edge Detector performed slightly better on Salt & Pepper noise than on Gaussian noise, its segmentation quality remained insufficient for practical applications. The low Dice, IoU, and SSIM values demonstrate its vulnerability to impulse-based noise artifacts. Conversely, U-Net consistently achieved perfect segmentation scores across all metrics, confirming its ability to extract meaningful features and ignore spurious noise patterns. Its structural understanding of images, supported by learned contextual features, makes it far more effective in handling scattered noise distortions compared to traditional pixel-gradient-based methods.

These results reinforce the importance of using deep learning models like U-Net in real-world applications where unpredictable noise conditions may otherwise compromise segmentation accuracy.

8. COMPARATIVE ANALYSIS OF TRADITIONAL AND DEEP LEARNING MODELS ON MOTION BLUR-AFFECTED DATASET

This section presents a comparison between the traditional Canny Edge Detection method and the deep learning-based U-Net model when applied to images degraded by Motion Blur. The evaluation is based on Dice Score, Intersection over Union (IoU), and Structural Similarity Index (SSIM) to analyze both the segmentation accuracy and visual consistency under motion-induced distortion. Motion Blur is particularly challenging because it smears edges and merges object boundaries, complicating the task of precise segmentation.

Dice Score Analysis

Canny Edge Detection (Traditional Model) - The Canny model achieved a Dice Score of **0.074** when evaluated on motion-blurred images. This extremely low score suggests that the model struggled significantly to detect accurate edges. The blurring effect reduced gradient sharpness across object boundaries, making it difficult for Canny's gradient-based approach to identify meaningful segmentation cues.

U-Net (Deep Learning Model) - In contrast, U-Net maintained a perfect Dice Score of **1.0** even under motion blur conditions. This indicates that U-Net was able to completely recover object boundaries despite the smearing introduced by motion. The result highlights the advantage of U-Net's multi-scale feature extraction and its ability to learn global spatial context, allowing it to "reconstruct" object shapes even from blurred inputs.

Intersection over Union (IoU) Analysis

Canny Edge Detection - The IoU score for Canny under motion blur was **0.038**, signifying minimal overlap between the predicted segmentation masks and the ground truth. The severely degraded IoU score further illustrates the model's inability to differentiate true object edges from blurred gradients.

U-Net - U-Net achieved an IoU score of **1.0**, perfectly matching the ground truth segmentation despite the distortion. This reinforces the Dice Score results and demonstrates the deep model's robustness against spatial degradations like motion blur.

Structural Similarity Index (SSIM) Analysis

Canny Edge Detection - The SSIM score for the Canny method was **0.160**, which is relatively higher compared to its SSIM scores under Gaussian and Salt & Pepper noise. However, this value remains low in an absolute sense, indicating poor visual similarity. This slight improvement in SSIM could be attributed to motion blur affecting larger regions uniformly, rather than introducing random pixel noise. U-Net - U-Net obtained an SSIM score of **0.314**, showing a significant improvement in perceptual similarity compared to the traditional model. Although motion blur impacts the visual clarity of the images, U-Net effectively maintained structural details essential for accurate segmentation.

When analyzing the results under motion blur, it is clear that deep learning models like U-Net offer a substantial advantage over traditional techniques. The near-zero Dice and IoU scores achieved by Canny indicate a near-complete failure in segmenting blurred images, underscoring the vulnerability of edge-based methods to motion-induced distortions. Despite slight improvements in SSIM, the overall segmentation output remained unreliable.

In stark contrast, U-Net preserved segmentation accuracy and visual coherence across all evaluation metrics. Its ability to integrate global context and learn deformation-invariant features allows it to handle challenging noise types like motion blur much more effectively.

These observations further emphasize that deep learning models, although computationally heavier, provide far superior robustness and adaptability for image segmentation in real-world, imperfect conditions.

CONCLUSION

This study conducted a comparative evaluation of two distinct approaches to image segmentation: the traditional Canny Edge Detection method and the deep learning-based U-Net model, with a specific focus on performance under noisy imaging conditions. By introducing Gaussian noise, Salt & Pepper noise, and Motion Blur into the Oxford-IIIT Pet dataset, we simulated real-world scenarios where input quality is often degraded. The goal was to assess how well each model could maintain segmentation accuracy and visual fidelity in the presence of distortions.

Our findings revealed a clear and consistent trend: the U-Net model significantly outperformed the Canny Edge Detection method across all types of noise. U-Net achieved perfect Dice Scores and Intersection over Union (IoU) values of 1.0 for each noise scenario, while Canny's performance remained considerably lower, particularly under Gaussian noise and Motion Blur. Even in relatively structured distortions like Salt & Pepper noise, Canny struggled to maintain reliable segmentation, whereas U-Net demonstrated strong resilience, accurately recovering object boundaries. In terms of perceptual evaluation using the Structural Similarity Index (SSIM), U-Net also achieved higher scores, reflecting better preservation of the structural integrity of segmented objects. While the expectation was that U-Net, given its sophisticated architecture and context-aware learning, would outperform the traditional method, the magnitude of difference was noteworthy. Canny's reliance on local gradient changes made it highly susceptible to random noise and blur, leading to fragmented and incomplete segmentations. U-Net, leveraging its encoder-decoder structure and skip connections, was able to preserve fine details even when global image quality deteriorated, highlighting the advantage of learned feature representations over rule-based methods.

The comparative analysis also reinforces important practical considerations. Although traditional methods like Canny are computationally efficient and easy to deploy, they are not suitable for applications where image quality cannot be guaranteed. On the other hand, deep learning models like U-Net, while requiring greater computational resources and training, offer far superior robustness, making them more suitable for real-world deployments where noise and distortions are inevitable.

In conclusion, this study demonstrates that deep learning-based segmentation models provide a substantial advantage over traditional techniques in noisy environments. U-Net's ability to maintain segmentation performance across varied and challenging conditions underlines the importance of adopting data-driven approaches in modern computer vision tasks. Future work may extend these findings by evaluating additional deep architectures, experimenting with more diverse noise patterns, or optimizing U-Net models for faster inference without compromising robustness. This research contributes valuable insights into model selection strategies for practical image segmentation tasks, emphasizing the critical role of robustness in real- world deployments.

REFERENCES

- S. Sahu, H. Sarma and D. Jyoti Bora, "Image Segmentation and its Different Techniques: An In-Depth Analysis," 2018 International Conference on Research in Intelligent and Computing in Engineering (RICE), San Salvador, El Salvador, 2018, pp. 1-7, doi: 10.1109/RICE.2018.8509038.
- Redford, Jesse, and Xingjie Li. "A feature oriented framework and enhanced assessments for imaging compression." 2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS). IEEE, 2020.
- Aithal, C.N., Ishwarya, P., Sneha, S., Yashvardhan, C.N., Kumar, D. and Suresh, K.V., 2021, November. Dynamic hand segmentation. In 2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) (pp. 1-6). IEEE.
- Singh, Ashutosh, Bulla Rajesh, and Mohammed Javed. "Deep learning based image segmentation directly in the jpeg compressed domain." In 2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), pp. 1-6. IEEE, 2021.
- Enriquez, M.L., Ducut, J.D., Concepcion, R., De Leon, J.A., Vicerra, R.R., Francisco, K., Relano, R.J., Bandala, A., Española, J., Co, H. and Reñosa, C.R., 2022, December. SubFuz: Subsurface Utility Detection Interface Employed Through Composite Fuzzy Clustering and Watershed Technique. In 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) (pp. 1-6). IEEE.
- Bhairnallykar, Sujata Tukaram, and Vaibhav Narawade. "Exploration of image segmentation: A comprehensive review of traditional segmentation techniques." 2023 7th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech). IEEE, 2023.
- Thakir, M. M. (2024, January). Quantifying Fractal-Based Features in Dermoscopic Images for Skin Cancer Characterization. In 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS) (pp. 1-5). IEEE.
- Prabu, S. & Gnanasekar, J.M.. (2021). A Study on Image Segmentation Method for Image Processing.

10.3233/APC210223.

- Khushmeen Kaur Brar, Bhawna Goyal, Ayush Dogra, Mohammed Ahmed Mustafa, Rana Majumdar, Ahmed Alkhayyat, Vinay Kukreja, Image segmentation review: Theoretical background and recent advances,Information Fusion,Volume 114,2025,102608,ISSN 1566-2535,https://doi.org/10.1016/j.inffus.2024.102608.(https://www.sciencedirect.com/science/article/pii/S15662535240 03865)
- Abdulateef, Salwa & Salman, Mohanad. (2021). A Comprehensive Review of Image Segmentation Techniques. Iraqi Journal for Electrical and Electronic Engineering. 17. 166-175. 10.37917/ijeee.17.2.18.
- Mohammed, Ali & Al-Ani, Laith. (2024). Modified Satellite Image Segmentation Based on Region Method. Al-Nahrain Journal of Science. 27. 81-87. 10.22401/ANJS.27.3.10.
- Shoaib, Asim & Vadiveloo, Mogana & Lim, Seng Poh. (2024). Comparative Studies of Region-Based Segmentation Algorithms on Natural and Remote Sensing Images. ITM Web of Conferences. 67. 10.1051/itmconf/20246701048.
- Boob, Archana & Radke, Mansi. (2024). Leveraging two- level deep learning classifiers for 2D shape recognition to automatically solve geometry math word problems. Pattern Analysis and Applications. 27. 10.1007/s10044-024-01321-9.
- Hanan, Sabbar. (2024). Overview of Medical Image Segmentation Techniques through Artificial Intelligence and Computer Vision. International Journal of Computing and Digital Systems. 15. 10.12785/ijcds/160183.
- Thottathil, Isaac Abraham, and S. Thivaharan. "Virtual Musical Instruments with Python and OpenCV." Journal of Ubiquitous Computing and Communication Technologies 5, no. 1 (2023): 1-20.
- Zhang, Tong, Huifeng Lin, Zhaojie Ju, and Chenguang Yang. "Hand Gesture recognition in complex background based on convolutional pose machine and fuzzy Gaussian mixture models." International Journal of Fuzzy Systems 22, no. 4 (2020): 1330-1341.
- Habib, M.T., Khatun, A., Aziz, M.A., Uddin, M.S. and Ahmed, F., 2021. An in-depth analysis of different segmentation techniques in automated local fruit disease recognition. Computer Vision and Machine Learning in Agriculture, pp.127-142.
- Yuan, Y., Cheng, Y. Medical image segmentation with UNet-based multi-scale context fusion. Sci Rep 14, 15687 (2024). https://doi.org/10.1038/s41598-024-66585-x
- Kugelman, J., Allman, J., Read, S.A. et al. A comparison of deep learning U-Net architectures for posterior segment OCT retinal layer segmentation. Sci Rep 12, 14888 (2022). https://doi.org/10.1038/s41598-022-18646-2
- David Gertsvolf, Miljana Horvat, Danesh Aslam, April Khademi, Umberto Berardi,A U-net convolutional neural network deep learning model application for identification of energy loss in infrared thermographic images,Applied Energy,Volume 360,2024,122696,ISSN 0306-2619,https://doi.org/10.1016/j.apenergy.2024.122696.(https://www.sciencedirect.com/science/article/pii/S0306261 924000795)
- Benchamardimath, Basavaprasad & Hegadi, Ravindra. (2014). A Survey on Traditional and Graph Theoretical Techniques for Image Segmentation. International Journal of Computer Applications. 38-46.
- Zhu, Haidong, Jialin Shi, and Ji Wu. "Pick-and-learn: Automatic quality evaluation for noisy-labeled image segmentation." In Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13– 17, 2019, Proceedings, Part VI 22, pp. 576-584. Springer International Publishing, 2019.
- Zhu, H., Shi, J., & Wu, J. (2019). Pick-and-learn: Automatic quality evaluation

for noisy-labeled image segmentation. In Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part VI 22 (pp. 576-584). Springer International Publishing.

- Vijaya Kishore, V., and V. Kalpana. "Effect of noise on segmentation evaluation parameters." In Soft Computing: Theories and Applications: Proceedings of SoCTA 2019, pp. 443-453. Singapore: Springer Singapore, 2020.
- Naz, Samina, Hammad Majeed, and Humayun Irshad. "Image segmentation using fuzzy clustering: A survey." In 2010 6th international conference on emerging technologies (ICET), pp. 181-186. IEEE, 2010.
- Akhlaghi, M. and Ichikawa, T., 2015. Noise-based detection and segmentation of nebulous objects. The Astrophysical Journal Supplement Series, 220(1), p.1.
- Pal, N. R., & Pal, S. K. (1993). A review on image segmentation techniques. Pattern recognition, 26(9), 1277-1294.
- Kaur, D., & Kaur, Y. (2014). Various image segmentation techniques: a review. International Journal of Computer Science and Mobile Computing, 3(5), 809-814.
- Haralick, Robert M., and Linda G. Shapiro. "Image segmentation techniques." Computer vision, graphics, and image processing 29, no. 1 (1985): 100-132.
- Bali, Akanksha, and Shailendra Narayan Singh. "A review on the strategies and techniques of image segmentation." In 2015 Fifth international conference on advanced computing & communication technologies, pp. 113-120. IEEE, 2015.
- Khan, Waseem. "Image segmentation techniques: A survey." Journal of image and graphics 1, no. 4 (2013): 166-170.
- Sharma, Neeraj, and Lalit M. Aggarwal. "Automated medical image segmentation techniques." Journal of medical physics 35, no. 1 (2010): 3-14.
- Bali, A., & Singh, S. N. (2015, February). A review on the strategies and techniques of image segmentation. In 2015 Fifth international conference on advanced computing & communication technologies (pp. 113-120). IEEE.
- Venu, D.N.D.A. and Kumar, A., 2021. Comparison of Traditional Method with watershed threshold segmentation Technique. The International journal of analytical and experimental modal analysis, 13, pp.181-187.
- Taneja, Arti, Priya Ranjan, and Amit Ujjlayan. "A performance study of image segmentation techniques." In 2015 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO)(Trends and Future Directions), pp. 1-6. IEEE, 2015.
- Yogamangalam, R., and B. Karthikeyan. "Segmentation techniques comparison in image processing." International Journal of Engineering and Technology (IJET) 5, no. 1 (2013): 307-313.
- Du, Getao, Xu Cao, Jimin Liang, Xueli Chen, and Yonghua Zhan. "Medical image segmentation based on U-net: A review." Journal of Imaging Science & Technology 64, no. 2 (2020).
- Siddique, Nahian, Sidike Paheding, Colin P. Elkin, and Vijay Devabhaktuni. "U-net and its variants for medical image segmentation: A review of theory and applications." IEEE access 9 (2021): 82031-82057.
- Alom, Md Zahangir, Mahmudul Hasan, Chris Yakopcic, Tarek M. Taha, and Vijayan K. Asari. "Recurrent residual convolutional neural network based on u-net (r2u-net) for medical image segmentation." arXiv preprint arXiv:1802.06955 (2018).
- Hore, A. and Ziou, D., 2010, August. Image quality metrics: PSNR vs. SSIM. In 2010 20th international conference on pattern recognition (pp. 2366-2369). IEEE.
- Gao, Yang, Abdul Rehman, and Zhou Wang. "CW-SSIM based image classification." In 2011 18th IEEE International Conference on Image Processing, pp. 1249- 1252. IEEE, 2011.
- Sara, U., Akter, M. and Uddin, M.S., 2019. Image quality assessment through FSIM, SSIM, MSE and PSNR—a comparative study. Journal of Computer and Communications, 7(3), pp.8-18.
- Guindon, B., & Zhang, Y. (2017).

Application of the dice coefficient to accuracy assessment of object-based image classification. Canadian Journal of Remote Sensing, 43(1), 48-61.

- Jha, Sudan, Raghvendra Kumar, Ishaani Priyadarshini, Florentin Smarandache, and Hoang Viet Long. "Neutrosophic image segmentation with dice coefficients." Measurement 134 (2019): 762-772.
- Wu, Shengkai, Jinrong Yang, Xinggang Wang, and Xiaoping Li. "Iou-balanced loss functions for single-stage object detection." Pattern Recognition Letters 156 (2022): 96-103.
- Cheng, Bowen, Ross Girshick, Piotr Dollár, Alexander C. Berg, and Alexander Kirillov. "Boundary IoU: Improving object-centric image segmentation evaluation." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 15334-15342. 2021.
- Minaee, Shervin, Yuri Boykov, Fatih Porikli, Antonio Plaza, Nasser Kehtarnavaz, and Demetri Terzopoulos. "Image segmentation using deep learning: A survey." IEEE transactions on pattern analysis and machine intelligence 44, no. 7 (2021): 3523-3542.
- Yanowitz, S.D. and Bruckstein, A.M., 1989. A new method for image segmentation. Computer Vision, Graphics, and Image Processing, 46(1), pp.82-95.