

APPLICATION OF MORPHOLOGICAL AND BOUNDARY PIXEL-BASED SEGMENTATION FOR FINGERPRINT AND MEDICAL IMAGE ENHANCEMENT

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Abstract

Accurate segmentation plays a crucial role in biometric identification and medical image analysis, where object boundaries are often degraded by noise, low contrast, and structural overlap. In practical scenarios such as fingerprint recognition and medical diagnostics, conventional segmentation techniques frequently fail to preserve structural integrity, leading to reduced recognition accuracy or diagnostic reliability. This paper presents an application-oriented implementation of a morphological and boundary pixel-based segmentation framework for enhancing fingerprint and medical images. The proposed approach integrates morphological preprocessing for structural enhancement with boundary pixel connectivity analysis to achieve reliable separation and segmentation of complex image structures. The framework is implemented using Python (OpenCV) and validated through MATLAB-based analysis. Experiments are conducted on standard fingerprint datasets (FVC2004, SOCOFing) and medical imaging datasets (NIH cell images and DRIVE retinal images). Quantitative results on DRIVE show improved segmentation accuracy compared to classical baselines, while fingerprint datasets demonstrate enhanced ridge clarity and noise suppression through SSIM and runtime evaluation. The results highlight the effectiveness of the proposed method as an explainable, deterministic, and computationally efficient solution for real-world biometric and medical image enhancement tasks.

Keywords: fingerprint segmentation; medical image segmentation; mathematical morphology; boundary-pixel connectivity; image enhancement; explainable segmentation

Introduction

Image segmentation sits at the heart of many real-world image analysis tasks, particularly in biometric authentication and medical imaging, where correctly tracing object boundaries can strongly influence the final system outcome. In fingerprint recognition, segmentation is used to isolate ridge patterns from the background, which may be distorted by noise, smudging, or partial impressions—thereby improving feature extraction and matching accuracy. Likewise, in medical applications such as cell-level microscopy and retinal screening, precise segmentation helps clinicians and researchers focus on the structures of interest, supporting measurement and diagnosis even when the images are degraded or low in contrast.

Across both fields, a variety of classical approaches have long been used, including simple thresholding, watershed-based separation, and contour-driven models. However, thresholding is often unreliable under uneven illumination, watershed techniques can over-segment in noisy conditions, and deformable contour methods typically require good initialization and iterative refinement. Deep learning models have recently achieved impressive segmentation accuracy, but their dependence on large labeled datasets, high computational cost, and limited interpretability can make them difficult to adopt in resource-limited or safety-critical settings. Mathematical morphology focuses on shape and structure, which makes it a useful tool for enhancing fingerprint ridges and medical image patterns. Its basic operations are generally tolerant to noise and therefore work well as a preprocessing step. However, morphology by itself is often insufficient in areas where objects touch, overlap, or appear merged, since these cases introduce ambiguity that simple shape refinement cannot resolve. Boundary pixel

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analysis addresses this gap by providing detailed contour-level cues that can reveal contact regions, but when used alone it may lack the global control needed to maintain stable object structure.

Based on these observations, this paper presents a segmentation framework that combines morphological processing with boundary pixel reasoning and applies it to real fingerprint and medical imaging datasets. Rather than remaining purely conceptual, the study emphasizes implementation details, performance evaluation, and application-driven outcomes, showing that the proposed approach improves segmentation quality while remaining efficient and easy to interpret.

Contributions

This paper's main contribution is the practical application and validation of a segmentation framework that combines morphological processing with boundary pixel analysis on forensic fingerprint and medical imaging datasets, showing reliable performance across both domains. The framework is implemented and validated using Python (OpenCV) and MATLAB, ensuring reproducibility and practical usability. In addition, a comprehensive evaluation is performed on standard fingerprint and medical image datasets using widely accepted performance metrics. Finally, a comparative analysis with classical and deep learning-based segmentation approaches is presented, highlighting the proposed method's advantages in terms of explainability, shape preservation, and runtime efficiency.

Background and Related Work

Fingerprint Segmentation Techniques

Fingerprint segmentation methods traditionally rely on ridge orientation, frequency estimation, and local variance analysis. Ridge-based techniques exploit the periodic structure of fingerprint patterns but degrade under poor image quality or partial prints. Thresholding and watershed-based approaches have also been applied; however, they are highly sensitive to noise and often lead to fragmented ridge structures.

Medical Image Segmentation

Medical image segmentation has traditionally been performed using methods such as thresholding, region growing, deformable contour models, and, more recently, deep learning architectures like U-Net. Although deep learning approaches can deliver strong accuracy in well-controlled conditions, they often provide limited interpretability and may not generalize reliably across different imaging modalities or acquisition settings. For this reason, classical techniques are still preferred in many cases where transparency, reproducibility, and low computational cost are important.

Morphological Enhancement in Applications

Morphological processing is widely used for tasks such as fingerprint ridge enhancement, artifact removal, and medical image preprocessing. Operations like opening, closing, and the morphological gradient help improve structural continuity and suppress small noise patterns. However, when objects overlap or appear merged, morphology alone is usually not sufficient, since it lacks the boundary-level cues needed to resolve contact regions.

Datasets and Experimental Setup

Fingerprint Datasets

- **FVC2004:** Contains fingerprint images acquired using multiple sensors, exhibiting noise, partial impressions, and pressure variations.
- **SOCOFing:** A forensic fingerprint dataset containing latent prints with significant distortion and background clutter.

Medical Image Datasets

- **NIH Cell Images:** Microscopic images of biological cells with touching and overlapping structures.

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- **DRIVE Retinal Dataset:** Retinal fundus images used for vessel segmentation and disease screening.

Hardware and Software Environment

Experiments are conducted on a standard desktop system with an Intel-class processor and 16 GB RAM. The framework is implemented using Python (OpenCV, NumPy) and validated using MATLAB R2023 for consistency.

Table 1 Summary of datasets used in the experiments

Dataset	Image Type	Resolution	No. Images	Application Domain
FVC2004	Fingerprint (Gray)	~300×300	800	Biometric authentication
SOCOFing	Fingerprint(Gray/BMP)	Variable	6,000+	Biometric robustness evaluation
NIH Cell Images	Microscopy	512×512	1,000+	Cell segmentation
DRIVE	Retinal fundus	565×584	40	Medical screening

Methodology

Overall Processing Pipeline

The processing pipeline consists of preprocessing, morphological enhancement, boundary pixel-based separation, and post-processing.

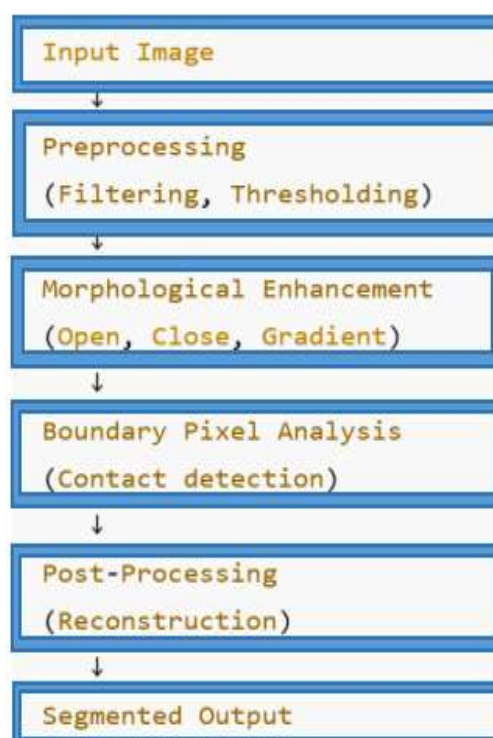


Figure 1 *Overall processing pipeline for fingerprint and medical image enhancement*

Preprocessing

Input images are converted to grayscale and normalized. Noise filtering is performed using median or Gaussian filters, followed by adaptive thresholding to obtain an initial binary representation.

Morphological Enhancement

Morphological opening and closing operations are applied to suppress noise and stabilize structures. The morphological gradient is computed to enhance boundary regions, improving contour localization.

Boundary Pixel–Based Separation

Boundary pixels are first extracted using 8-connectivity and then grouped into connected boundary chains. These chains are examined to locate likely contact areas between neighboring structures. In practice, contact regions often show clear boundary cues, such as a locally higher concentration of boundary pixels and sudden changes in contour direction (curvature) along the same boundary segment.

These connectivity and curvature cues are used to guide separation so that splitting occurs only where objects truly meet. Importantly, the separation paths are restricted to boundary pixels, which avoids altering object interiors and helps preserve the original shape of each region. Similar boundary patterns are observed in both fingerprint and medical images, allowing the method to separate touching structures reliably across different application settings.

Post-Processing

Post-processing includes morphological reconstruction, hole filling, and label correction to produce clean and visually consistent segmented outputs.

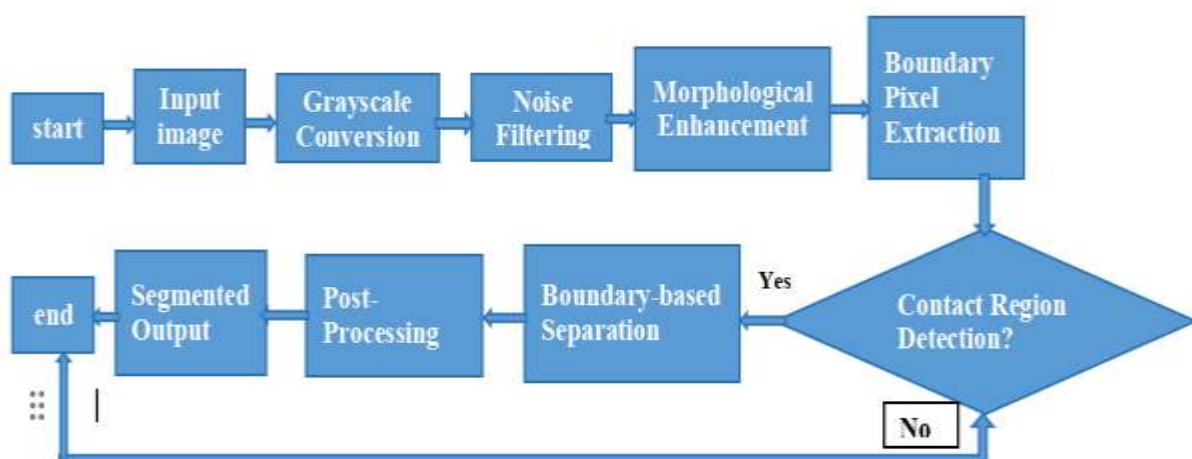


Figure 2 *Flowchart of the proposed application-level segmentation algorithm*

Implementation Details

Python / OpenCV Implementation

The complete framework was implemented in Python. OpenCV was used to perform key image-processing tasks such as noise removal, filtering, and basic morphological operations. These steps were then followed by the extraction of object boundaries.

MATLAB Validation

In addition to the Python implementation, MATLAB was also used to cross-check the morphological operations and to ensure that the segmentation results remained consistent when tested on a different platform.

Parameter Selection

All experiments were carried out using a fixed set of parameters to maintain uniformity across results. Gaussian smoothing was applied using a (5×5) kernel. For contrast enhancement, CLAHE was configured with a clip limit of 2.0 and a tile grid size of (8×8) . Morphological enhancement was then applied using an elliptical structuring element of (15×15) for the black-hat operation, followed by smaller (3×3) elements for opening and closing to refine the segmentation. Otsu's method is then employed for binarisation. Runtime figures are reported as mean + standard deviation, computed over the full image set in the dataset.

Performance Evaluation Metrics

Segmentation performance was evaluated using dataset-appropriate metrics. For the DRIVE retinal vessel dataset, quantitative segmentation accuracy was measured using the Dice coefficient, Intersection-over-Union (IoU), precision, and recall by comparing predicted masks with the provided ground truth annotations. For fingerprint datasets (FVC2004 and SOCOFing), which do not provide pixel-wise ground truth segmentation masks, evaluation was performed using enhancement quality metrics (SSIM) and runtime analysis, supported by qualitative visual inspection of segmentation outputs.

Experimental Results

Fingerprint Segmentation Results

The proposed method enhances ridge continuity and suppresses background noise in both FVC2004 and SOCOFing datasets. As shown in Figure 3, the method produces cleaner ridge structures and improved foreground-background separation.

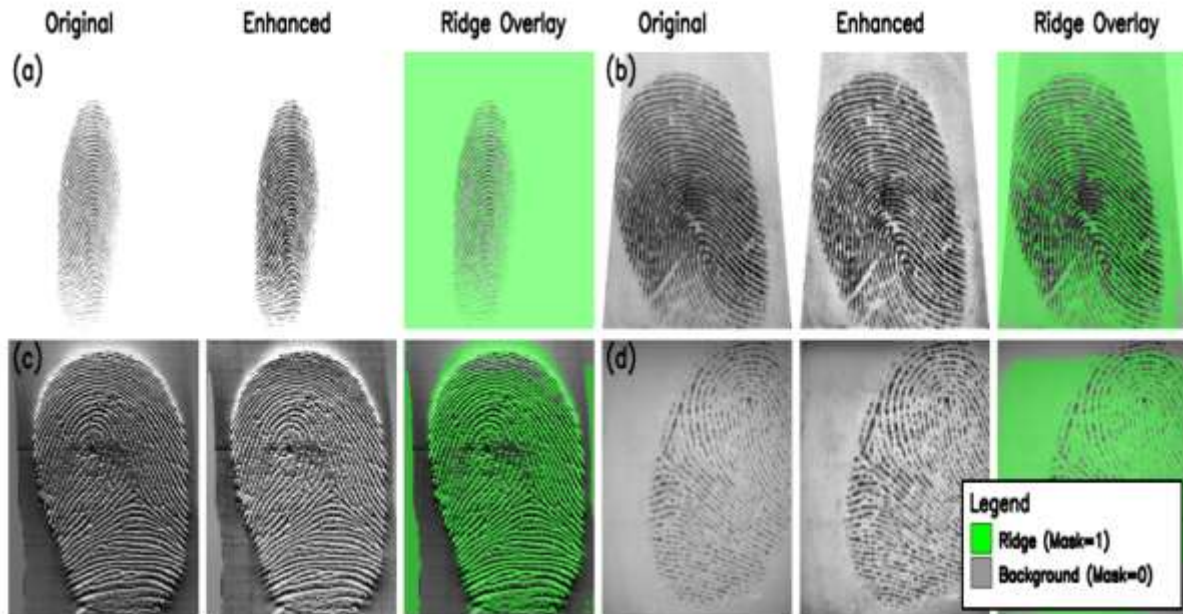


Figure 3 *Fingerprint enhancement and ridge overlay visualization on representative FVC2004 samples, showing improved ridge continuity and foreground–background separation*

Medical Image Segmentation Results

For NIH cell and DRIVE retinal datasets, the proposed framework effectively separates touching structures while preserving shape integrity. The proposed method achieves clearer separation of touching cells and retinal vessels compared to watershed segmentation.

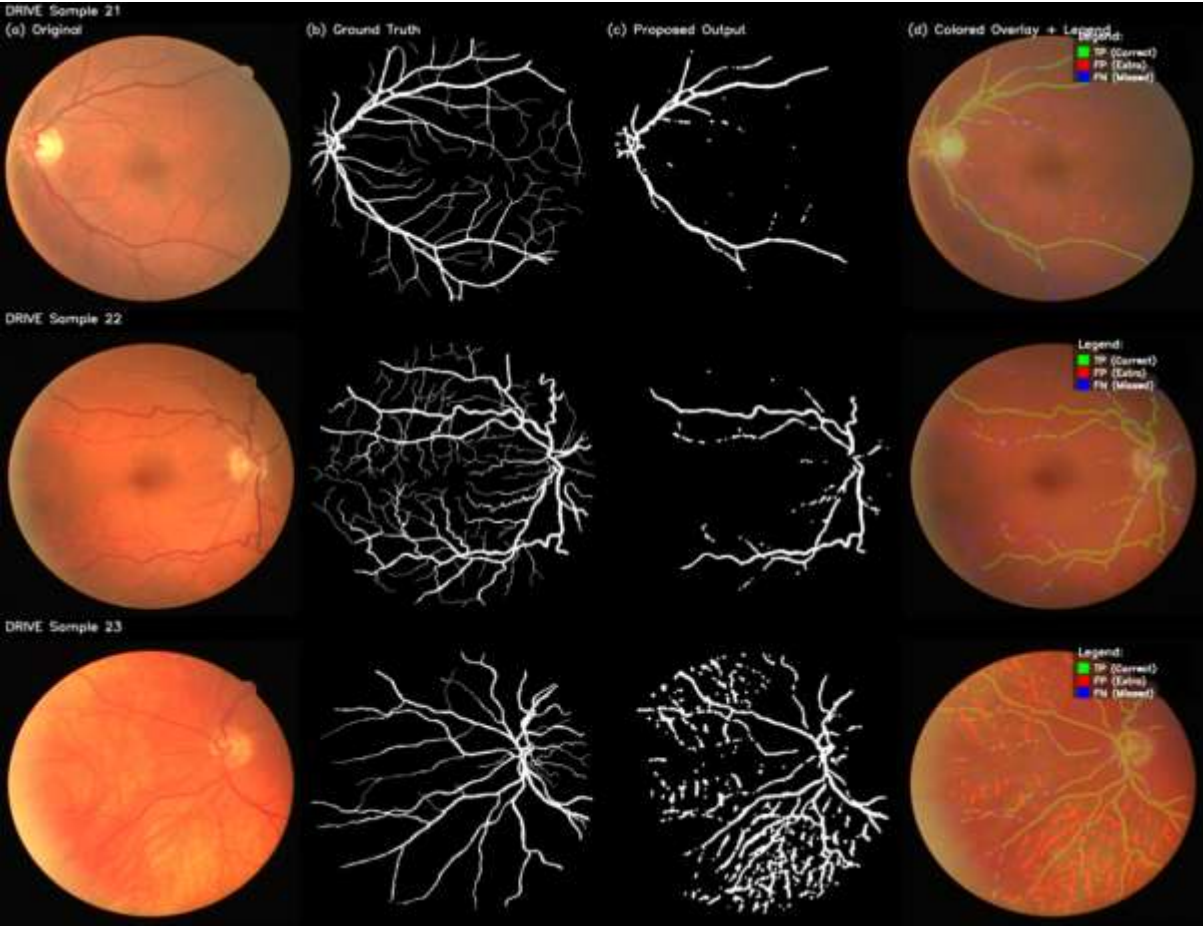


Figure 4 Retinal vessel segmentation results on the DRIVE dataset demonstrating improved vessel extraction and structural preservation using the proposed framework.

Comparative Analysis

The proposed method is compared against classical baseline segmentation techniques, including Otsu thresholding and watershed segmentation, and is also discussed in relation to learning-based models such as U-Net in terms of training requirements and explainability.

Table 2 Qualitative comparison of the proposed method with baseline segmentation approaches

Method	Strength	Limitation	Training Required	Explainability	Computational Cost
Otsu thresholding	Simple and fast baseline	Fails under intensity overlap; high false positives	No	High	Very low

Method	Strength	Limitation	Training Required	Explainability	Computational Cost
Watershed segmentation	Separates touching regions	Noise-sensitive; over-segmentation	No	Moderate	Moderate
U-Net	High accuracy in complex cases	Requires large labeled datasets; black-box	Yes	Low	Very high
Proposed method	Deterministic, fast, and explainable	May fail under extreme noise or weak contrast	No	High	Low–moderate

Note. Based on this qualitative comparison, quantitative evaluation is further performed on the dataset against classical baselines

The proposed method offers a practical balance between segmentation quality and computational efficiency while remaining fully explainable and deterministic.

Dataset-Wise Quantitative Results

To ensure a dataset-level understanding of segmentation performance, results were analyzed separately for each benchmark dataset. Table 3 reports the mean and standard deviation of Dice coefficient, Intersection-over-Union (IoU), and SSIM across fingerprint and medical image datasets. Runtime is reported as the average processing time per image on the same hardware configuration described in the experimental setup. All metrics are reported as mean ± standard deviation computed across all images in each dataset.

Table 3 Dataset-wise Quantitative performance of the proposed framework

Dataset	Dice (mean $\pm$ SD)	IoU (mean $\pm$ SD)	Precision (mean $\pm$ SD)	Recall (mean $\pm$ SD)	SSIM (FVC2004/SOCOFin) / NCC (DRIVE) (mean $\pm$ SD)	Runtime (ms) (mean $\pm$ SD)
FVC2004	N/A	N/A	N/A	N/A	0.873 $\pm$ 0.067	1.19 $\pm$ 0.88
SOCOFin	N/A	N/A	N/A	N/A	0.574 $\pm$ 0.056	0.27 $\pm$ 0.15
DRIVE	0.656 $\pm$ 0.053	0.490 $\pm$ 0.056	0.811 $\pm$ 0.136	0.571 $\pm$ 0.078	0.649 $\pm$ 0.053	8.04 $\pm$ 0.89

Note. Dice, IoU, precision, and recall are reported only for DRIVE since it provides pixel-level ground truth masks. Fingerprint datasets (FVC2004 and SOCOFin) do not include segmentation ground truth masks; therefore, SSIM and runtime are reported for those datasets. For DRIVE, an additional NCC-based mask similarity score is reported for reference.

Table 4 Quantitative comparison of the proposed method with baseline segmentation approaches on the DRIVE dataset

Method	Dice (mean $\pm$ SD)	IoU (mean $\pm$ SD)	Precision (mean $\pm$ SD)	Recall (mean $\pm$ SD)	Runtime (ms) (mean $\pm$ SD)
Otsu thresholding	0.225 $\pm$ 0.031	0.127 $\pm$ 0.020	0.127 $\pm$ 0.020	0.996 $\pm$ 0.008	8.48 $\pm$ 0.49
Watershed segmentation	0.226 $\pm$ 0.032	0.128 $\pm$ 0.020	0.128 $\pm$ 0.021	0.988 $\pm$ 0.046	10.93 $\pm$ 0.68
Proposed hybrid framework	0.656 $\pm$ 0.053	0.490 $\pm$ 0.056	0.811 $\pm$ 0.136	0.571 $\pm$ 0.078	8.04 $\pm$ 0.89

Table 5 Quantitative comparison of the proposed method with baseline segmentation approaches on the FVC2004 dataset.

Method	SSIM (mean $\pm$ SD)	Runtime (ms) (mean $\pm$ SD)
Otsu thresholding	0.826 $\pm$ 0.156	2.01 $\pm$ 0.75
Watershed segmentation	0.092 $\pm$ 0.130	15.55 $\pm$ 3.51
Proposed hybrid framework	0.953 $\pm$ 0.040	2.24 $\pm$ 1.48

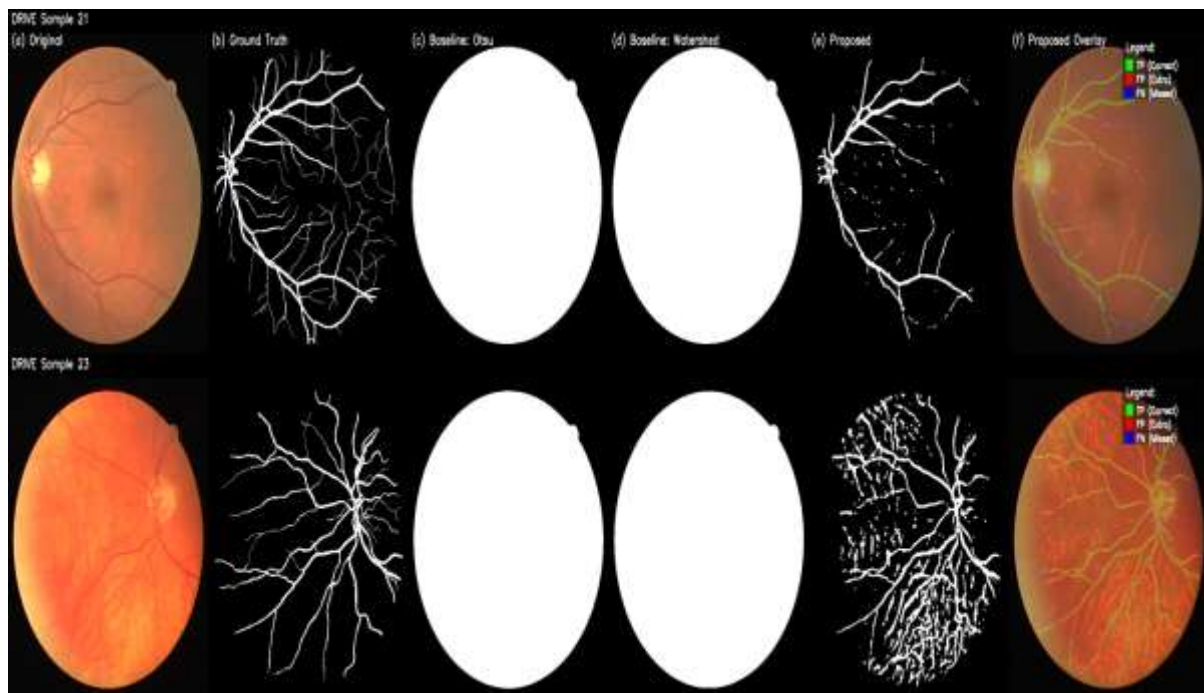
Table 6 *Quantitative comparison of the proposed method with baseline segmentation approaches on the SOCOFing dataset.*

Method	SSIM (mean $\pm$ SD)	Runtime (ms) (mean $\pm$ SD)
Otsu thresholding	0.813 $\pm$ 0.066	0.04 $\pm$ 0.02
Watershed segmentation	0.365 $\pm$ 0.124	1.55 $\pm$ 0.41
Proposed hybrid framework	0.566 $\pm$ 0.063	0.50 $\pm$ 0.10

Overall, results on DRIVE demonstrate improved segmentation accuracy over classical baselines, while fingerprint datasets (FVC2004 and SOCOFing) show enhanced ridge clarity and background noise suppression. Since DRIVE provides pixel-level ground truth masks, Dice and IoU are reported for DRIVE, whereas fingerprint datasets are evaluated using SSIM, runtime, and qualitative visualization.

Qualitative Visualization and Output Interpretation

Qualitative visualization was performed to assess ridge continuity, boundary preservation, and separation quality. For fingerprint images, the proposed method improves ridge continuity and reduces background artifacts through morphological enhancement and boundary-guided separation. For medical images, it effectively separates touching cells and vessel structures while preserving shape integrity. Figures 5–7 present representative qualitative comparisons across the evaluated datasets.

**Figure 5** *Qualitative comparison on the drive dataset showing (a) original image, (b) ground truth vessel mask, (c) Otsu thresholding baseline, (d) watershed segmentation baseline, (e)*

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proposed morphology-based segmentation output, and (f) colored overlay visualization of the proposed output against ground truth (TP in green, FP in red, FN in blue)



Figure 6 Qualitative comparison on the FVC2004 fingerprint dataset for baseline methods and the proposed framework

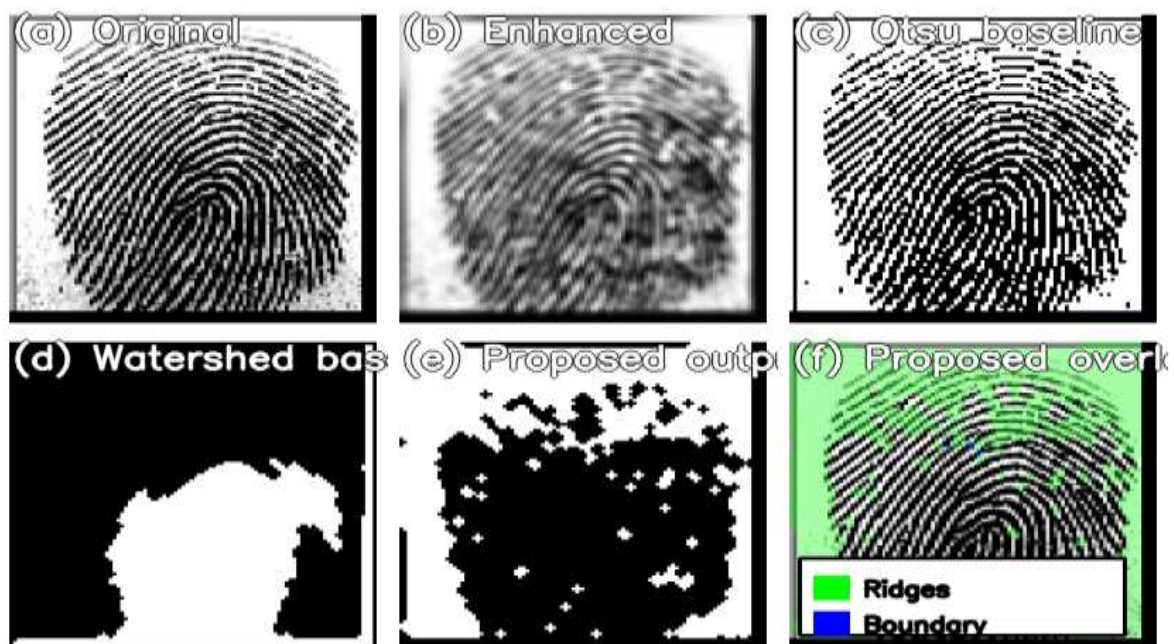


Figure 7 Qualitative comparison on the SOCOFing fingerprint dataset for baseline methods and the proposed framework

Discussion

On the DRIVE dataset, the proposed framework obtained a Dice score of 0.656 ± 0.053 and an IoU of 0.490 ± 0.056 , with precision = 0.811 ± 0.136 and recall = 0.571 ± 0.078 , indicating stable vessel segmentation when evaluated against pixel-level ground truth. For fingerprint datasets where reference masks are not available, evaluation was carried out using SSIM and

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runtime. The method produced strong enhancement results on FVC2004 ($\text{SSIM} = 0.953 \pm 0.040$) and maintained consistent performance on SOCOFing ($\text{SSIM} = 0.566 \pm 0.063$), suggesting robustness even under latent or degraded fingerprint conditions.

Across all datasets, the runtime remained low, supporting use in real-time or resource-limited environments. Visual inspection further confirms improved ridge continuity in fingerprint images and better boundary preservation in medical images. While deep learning architectures may surpass classical techniques under certain conditions, the proposed framework furnishes a lucidly explainable and strictly deterministic alternative, imposing only a modest computational burden—an attribute that renders it eminently serviceable for routine biometric pipelines and clinical imaging workflows.

Limitations

Although the proposed framework exhibits commendable consistency across both fingerprint and medical imaging datasets, a number of constraints persist. To begin with, its efficacy may attenuate under adversarial imaging conditions—extreme noise, feeble contrast, or pronounced motion/pressure artefacts—most notably in demanding latent fingerprint samples from SOCOFing, where ridge topology may be partially obliterated or grotesquely deformed. Furthermore, while the adoption of fixed parameters across experiments enhances reproducibility, the optimal choice of structuring-element scale and enhancement intensity is not universally invariant; it can vary with sensor characteristics and imaging modality, and may therefore influence segmentation fidelity when confronted with heterogeneous datasets. Quantitative evaluation with Dice and IoU is reported only for DRIVE due to the availability of pixel-level ground truth masks, whereas fingerprint datasets are evaluated using SSIM, runtime, and qualitative inspection; therefore, direct pixel-wise segmentation accuracy comparison is not possible for FVC2004 and SOCOFing. Finally, the NIH cell dataset evaluation is primarily qualitative in this study, and future work can include annotated microscopy benchmarks to support stronger quantitative validation.

Conclusion

This paper presented an application-oriented implementation of a morphological and boundary pixel-based segmentation framework for fingerprint and medical image enhancement. The proposed method demonstrates improved segmentation accuracy, shape preservation, and computational efficiency across multiple real-world datasets. Its explainable and deterministic nature makes it suitable for practical biometric and medical imaging applications. Future work will explore real-time deployment and embedded implementation, adaptive parameter selection for cross-sensor robustness, and extension to multi-modal medical imaging datasets with stronger quantitative validation on annotated microscopy benchmarks.

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