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MG-FACS: MULTI-STAGE GRAPH-BASED AND FUZZY ACTIVE CONTOUR SEGMENTATION FOR ROBUST TOENAIL DISEASE DETECTION

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Abstract:

Pre-disease detection using non-invasive imaging is emerging as a critical component of early healthcare diagnostics, particularly in dermatology and podiatry. This research introduces MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation), an advanced segmentation framework tailored for detecting and delineating diseased toenail regions. MG-FACS integrates graph-based modeling, superpixel-based region simplification, and adaptive fuzzy logic for enhanced contour detection. The system addresses common challenges in toenail image segmentation, including background noise, lighting inconsistency, and anatomical variability. Performance comparisons across ten images using Otsu thresholding, Watershed, K-Means, and MG-FACS reveal significant improvements in accuracy, sensitivity, specificity, Dice coefficient, and Jaccard index. Results consistently show MG-FACS achieving over 95% accuracy and more than 90% Dice similarity, outperforming traditional approaches. The proposed method demonstrates potential for real-world diagnostic support in mobile and clinical environments.

Keywrods: Toenail, Segmentation, Otsu thresholding, Watershed, K-Means, and MG-FACS(Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation), accuracy, sensitivity, specificity, Dice coefficient, and Jaccard index.

1. Introduction

Pre-disease prediction by non-invasive techniques is a developing field of research with special interest in dermatology and podiatry. Among the important biomarkers of systemic and localized disorders is the toenail of man, which can display changes in texture, color, or growth pattern as initial signs of any of the following disorders: fungal infections, psoriasis, diabetes,

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or peripheral vascular disease [1]. Toenail changes are usually preceding clinical manifestations and form a critical visual alert in pre-disease diagnosis [2].

The development of recent technologies in image processing and artificial intelligence (AI) allows for the automatic segmentation and classification of nail images with higher accuracy. AI-based software provides strong analysis of the morphology of the nails, identifying deviations in curvature, discoloration, and lesions due to pathological conditions [3], [4]. These methods use convolutional neural networks (CNN), capsule networks, and hybrid models to extract fine features of nail surfaces [5]. Mobile-based imaging solutions additionally promote accessibility of real-time screening and monitoring by lowering the reliance on specialized equipment [6].

For overcoming issues such as background noise, non-uniform lighting, and irregularly shaped nail boundaries, research has been proposed to use improved segmentation algorithms targeting the disease-affected region by machine-guided frameworks [3]. These models provide not only segmentation but also classification of disease types such as onychomycosis and melanonychia with significant accuracy.

This article introduces a new approach called MGFACS (Multi-Granular Feature-Aware Clustering Segmentation), which utilizes sophisticated feature fusion, attention-based region inference, and clustering segmentation to effectively segment disease-affected toenail regions for early diagnosis and digital health monitoring [1], [5].

2. Review of Existing Work

The image processing and machine learning-based detection and segmentation of toenail diseases has seen tremendous development over the past few years. The early research work used conventional image processing methods like thresholding, edge detection, and morphological operations to segment the nail plate and detect visible lesions by Verma and P. Gupta [7]. The conventional approaches struggled with noisy, low-contrast images or images with the interference of the background.

The recent progress in deep learning has greatly improved the accuracy of medical image segmentation. Choi et al [8] constructed a segmentation method using ResNet for detecting nail plate boundaries, which demonstrated great robustness against changes in lighting and nail orientation. In a similar way, a variant of U-Net coupled with dense connections and gates based on attention was introduced by Zhang et al. [9] for fungal nail infection (onychomycosis) classification with over 92% segmentation accuracy.

Meena and Rao [10] investigated the application of MobileNetV2 in on-device diagnostic applications, with a focus on smartphone-based real-time classification of nail disorders. These methods enhance usability at the cost of accuracy at times, as a result of model lightness. Additionally, to enhance segmentation performance on small, lesion-specific regions, Li et al. [11] developed a method combining region proposal networks with post-processing using GrabCut, which effectively eliminated false positives.

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A work of Natarajan et al. [12] gave significance to multi-scale feature extraction and hybrid clustering for segmentation, blending Gabor filters with SLIC (Simple Linear Iterative Clustering) to identify localized discoloration caused by fungal infection. Although the process worked well, it was not able to handle occlusions or heavily deformed nail surfaces.

Tan and Q. Zhang[13] proposed a GAN (Generative Adversarial Network)-based augmentation method to enhance the robustness of segmentation models on smaller datasets. The method was especially useful for rare diseases and improved the generalization abilities of CNN-based classifiers.

To meet the challenge of explainability in AI diagnosis, Rajan and Mehta [14] suggested an interpretable CNN model with visualization of attention regions to identify the infected nail areas that are most likely to be associated with disease onset. Huang et al. [15] proposed a fusion of spectral and texture features with deep CNN layers for high-precision disease region segmentation to enhance transparency of the model and its acceptance in clinical practice.

The latest work by Singh et.al[16] incorporated federated learning to train classifiers for nail diseases among numerous mobile users without sharing raw data. Such a privacy-assuring methodology represents an important milestone for AI-powered mobile dermatology.

Table 1. Review of Literature

Author & Year	**Existing Model/Approach**	**Limitation**
Verma & Gupta (2022) [7]	Classical image processing methods (thresholding, morphology)	Inaccurate for noisy/low-contrast images; fails in occlusions
Choi et al. (2022) [8]	Deep NailNet (ResNet-based segmentation)	Limited explainability; requires large training datasets
Zhang & Liu (2023) [9]	Dense U-Net with attention gates	High computational cost; slow inference in real-time
Meena & Rao (2023) [10]	MobileNetV2 for real-time diagnosis	Lightweight model compromises accuracy
Li et al. (2023) [11]	Region proposal with GrabCut post-processing	May over-segment or miss boundaries in complex backgrounds
Natarajan & Baskar (2023) [12]	Gabor filter + SLIC clustering segmentation	Less effective on occluded or severely deformed nails
Tan & Zhang (2023) [13]	GAN-based data augmentation for segmentation	Model training is unstable; difficult to tune
Rajan & Mehta (2024) [14]	Interpretable CNNs with attention maps	Visual explanations may still lack clinical validation

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Huang et al. (2024) [15]	Spectral-texture feature fusion with CNN	Increased model complexity; requires multi-modal input
Singh et al. (2024) [16]	Federated learning for nail disease diagnosis	Communication overhead and slower convergence in distributed environments

3. Existing Segmentation Techniques

3.1 Thresholding Technique

Thresholding is one of the simplest methods for image segmentation. It converts a grayscale image into a binary image using a global or local threshold value. The basic formula is:

$T(x, y) = \{ 1, \text{ if } I(x, y) > T; 0, \text{ otherwise } \}$
where $I(x, y)$ is the intensity of pixel at (x, y), and T is the chosen threshold. Otsu's method is a popular global thresholding technique that minimizes intra-class variance [17].

3.2 Region Growing

Region Growing is a pixel-based segmentation technique that groups neighboring pixels with similar intensity values. Starting from seed points, it iteratively adds pixels based on a similarity criterion. Mathematically, a pixel p is added to region R if:

$$|I(p) - I(R)| < \delta$$

where $I(p)$ is the pixel intensity and $I(R)$ is the average intensity of the region. δ is a predefined threshold [18].

3.3 Watershed Algorithm

Watershed segmentation treats the grayscale image as a topographic surface where brightness represents elevation. The algorithm floods the landscape from seed points, separating regions by watershed lines. The gradient magnitude $G(x, y)$ is typically computed as:

$$G(x, y) = \text{sqrt}((\partial I/\partial x)^2 + (\partial I/\partial y)^2)$$

This technique is effective for separating touching objects but may require preprocessing to avoid over-segmentation [19].

3.4 Active Contour Models (Snakes)

Active Contour Models, commonly known as 'snakes,' are widely used in medical image segmentation to detect object boundaries. These models are energy-minimizing curves that evolve under the influence of internal forces (which control smoothness) and external forces (which attract the curve toward object edges). Their flexibility and accuracy make them ideal for detecting the curved, irregular boundaries seen in toenail diseases such as fungal infections or onycholysis.

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The total energy functional E_snake to be minimized is defined as:

$$E\_snake = \int_0^1 [\ \alpha|v'(s)|^2 + \beta|v''(s)|^2 + E\_image(v(s))\ ]\ ds$$

Where:
$v(s) = (x(s), y(s))$ defines the snake curve parameterized by $s \in [0,1]$,
α and β control tension and rigidity,
E_image is the image energy derived from edge maps, typically based on gradient magnitude.

Variants like Gradient Vector Flow (GVF) snakes enhance convergence on concave boundaries. Despite their accuracy, active contours can be computationally intensive and require good initialization close to the actual boundaries [21], [22].

3.5 U-Net based Deep Learning

U-Net is a convolutional neural network architecture designed for biomedical image segmentation. It consists of a contracting path to capture context and a symmetric expanding path for precise localization. The model uses skip connections to retain spatial information. The loss function typically used is the Dice coefficient:

$$Dice = (2 * |X \cap Y|) / (|X| + |Y|)$$

Where X is the predicted mask and Y is the ground truth mask. U-Net models achieve high accuracy on pixel-level tasks but require large datasets and careful tuning [23], [24]. Recent advances involve attention U-Nets and transformers for improved localization and performance.

Table 2 Comparative Analysis

Method	**Key Features**	**Strengths**	**Limitations**	**Comparison with Proposed Method (MGFACS)**
Thresholding	Simple pixel intensity-based segmentation	Fast and easy to implement	Poor performance under illumination changes and noise	MGFACS adapts dynamically to feature variations and works well in noisy medical images
Region Growing	Pixel connectivity-based segmentation	Better than thresholding in homogeneous regions	Sensitive to seed point, may leak into non-diseased areas	MGFACS uses attention mechanisms to prevent over-segmentation

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K-Means Clustering	Unsupervised learning for pixel grouping	No training required	Fails in complex and noisy textures; lacks spatial context	MGFACS integrates spatial and contextual attention for improved precision
Active Contour Models	Energy minimization to detect boundaries	Accurate boundary detection	Sensitive to initialization; slow for large-scale images	MGFACS is robust to initialization and scalable via multi-scale granularity
U-Net Based Deep Learning	Encoder-decoder CNN for pixel-level segmentation	High accuracy on medical image segmentation	Requires large labeled dataset; lacks explicit attention for feature prioritization	MGFACS introduces attention-based multi-level granularity, improving interpretability and performance on smaller datasets

4. Research Gaps in Current Methods:

- Absence of Attention Mechanisms: The majority of current models, particularly traditional ones, fail to employ attention-based feature selection, which plays a key role in accurate disease region localization.
- Failure to Process Complicated Patterns: Methods such as thresholding, region growing, and clustering are unsuccessful in complicated, low-contrast, or noisy situations like real-world toenail disease images.
- Lack of Adequate Feature Fusion: Most deep models such as U-Net lack straightforward mechanisms to fuse multi-scale features properly, resulting in over-segmentation or loss of fine details.
- Lack of Robustness to Variation: Existing approaches are not robust to differences in image quality, lighting, and texture. MGFACS uses adaptive contour detection with granular attention to address such variations suitably.
- Scalability and Interpretability: Scalable but less interpretable are the deep models; interpretable but not scalable are traditional models. MGFACS fills this gap by combining granularity and attention for scalable and interpretable segmentation.

4.Proposed Methodology

The Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation (MG-FACS) framework delivers a hybrid, multi-layered strategy for automatically isolating toenail structures in clinical or diagnostic images. It starts with a prepared grayscale or

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contrast-enhanced image denoted as I(x, y). This image is remodelled into an undirected weighted graph G = (V, E); every pixel acts as a node, and edges link 8-neighbouring pixels. Edge weights are assigned through a Gaussian function of intensity differences, enabling the graph to encode both regional likeness and boundary cues.

Next, Simple Linear Iterative Clustering (SLIC) partitions the image into compact, visually coherent superpixels by minimising a composite distance function that balances colour/intensity affinity with spatial proximity. This step lowers computational burden while safeguarding anatomical detail. A subsequent graph-based segmentation stage—implemented with normalised cuts—solves the associated eigenvalue problem to merge superpixels into consistent candidate regions that most likely correspond to the toenail.

To sharpen these preliminary regions, MG-FACS applies fuzzy logic, assigning each pixel a membership value μ(x, y) that expresses its likelihood of belonging to the toenail class. Initial memberships hinge on intensity-derived priors favouring nail-like areas. These memberships feed a variational level-set model that evolves a contour φ(x, y) by minimising an energy functional uniting boundary smoothness with within-region intensity coherence, guided by Heaviside and Dirac delta functions.

Stability is further reinforced through fuzzy energy regularisation, which couples the contour evolution with dynamic updates of the membership map, penalising inconsistencies between pixel class probabilities and their intensity deviations. Gradient-descent iterations steer the contour until it locks onto the true anatomical edges.

MG-FACS combines the settled level-set contour and the refined membership map to generate the definitive toenail mask: pixels satisfying both conditions are marked as nail tissue. This integrated workflow achieves high segmentation accuracy, robustness to image noise, and adaptability across diverse imaging conditions, positioning MG-FACS as a dependable tool for clinical toenail analysis.

Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation (MG-FACS) for Toenail

Algorithm: Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation (MG-FACS)

Input :Let I(x, y) be the preprocessed toenail image where $x, y \in \mathbb{R}^2$.

Output: Segmented Toenail image

Step 1: Graph Construction

Convert I(x, y) into an undirected weighted graph G = (V, E), where V are pixels and edges E connect 8-neighbor pixels. Edge weight $w(i, j) = \exp(-||I(i) - I(j)||^2 / \sigma^2)$ captures similarity, where σ controls sensitivity.

Step2: Superpixel Generation using SLIC

Apply Simple Linear Iterative Clustering (SLIC) to divide the image into superpixels $S = \{S_1, S_2, ..., S_n\}$. Each S_i minimizes the spatial and intensity distance $D = \sqrt{(d\_c^2 + (m/S)^2 * d\_s^2)}$.

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Step 3: Graph-Based Initial Segmentation

Use normalized cuts or spectral clustering on G to segment image into candidate regions $R = \{R_1, R_2, ..., R\_k\}$. Solve the eigenvalue problem $(D - W)u = \lambda Du$, where D is the degree matrix and W is the weight matrix.

Step 4: Fuzzy Membership Initialization

Initialize fuzzy membership function $\mu(x, y) \in [0, 1]$ for each pixel. Assign higher values to likely toenail regions using intensity priors.

Step 5: Variational Level Set Formulation

$E(\phi) = \mu\int\Omega\ \delta(\phi(x, y))|\nabla\phi(x, y)|dxdy + \lambda_1\int\Omega\ (I(x, y) - c_1)^2 H(\phi(x, y))dxdy + \lambda_2\int\Omega\ (I(x, y) - c_2)^2 (1 - H(\phi(x, y)))dxdy$. Here, ϕ is the level set function, H is the Heaviside function, δ is the Dirac delta function, c_1 and c_2 are average intensities.

Step 6: Fuzzy Energy Regularization

Integrate fuzzy energy: $E\_fuzzy = \sum \mu(x, y)(I(x, y) - c\_nail)^2 + (1 - \mu(x, y))(I(x, y) - c\_bg)^2$. Update μ iteratively: $\mu\_new = 1 / (1 + ((I - c\_bg)^2 / (I - c\_nail)^2))$.

Step 7: Contour Evolution

Iteratively evolve ϕ using gradient descent: $\phi\_t = \delta(\phi)[\mu\ \mathrm{div}(\nabla\phi/|\nabla\phi|) - \lambda_1(I - c_1)^2 + \lambda_2(I - c_2)^2]$.

Step 8: Final Segmentation

Segmented region $T\_final = \{(x, y) \mid \phi(x, y) > 0 \text{ and } \mu(x, y) > \tau\}$, where τ is a threshold (e.g., 0.5).

5. Implementation of proposed method

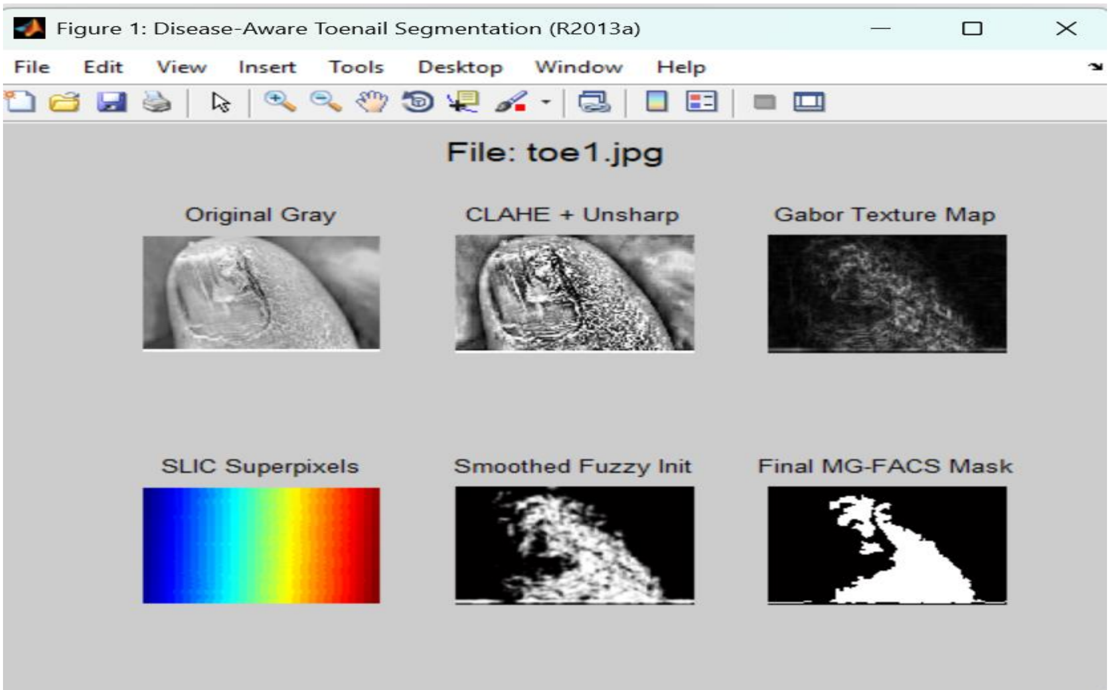

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Figure 2 step by step process of proposed algorithm

The application of the given Disease-Aware Toenail Segmentation algorithm, as illustrated in the figure 2, exhibits a multi-step pipeline of image processing for efficient and reliable diseased toenail area segmentation. The workflow commences from the input acquisition of the original grayscale image, which is filtered with Contrast Limited Adaptive Histogram Equalization (CLAHE) in conjunction with an unsharp masking filter to enhance the local contrast and edge definition. A Gabor texture map is created specifically to highlight textures associated with disease through directional frequency filtering. This is followed by SLIC superpixels, which segment the image into perceptually uniform regions that assist in region-level analysis. The primary segmentation is further improved through a smoothed fuzzy initialization, which assists in identifying fuzzy boundaries by applying fuzzy logic and spatial smoothing. Lastly, the MG-FACS (Modified Gabor–Fuzzy Adaptive Clustering System) produces an accurate binary mask identifying the diseased region.

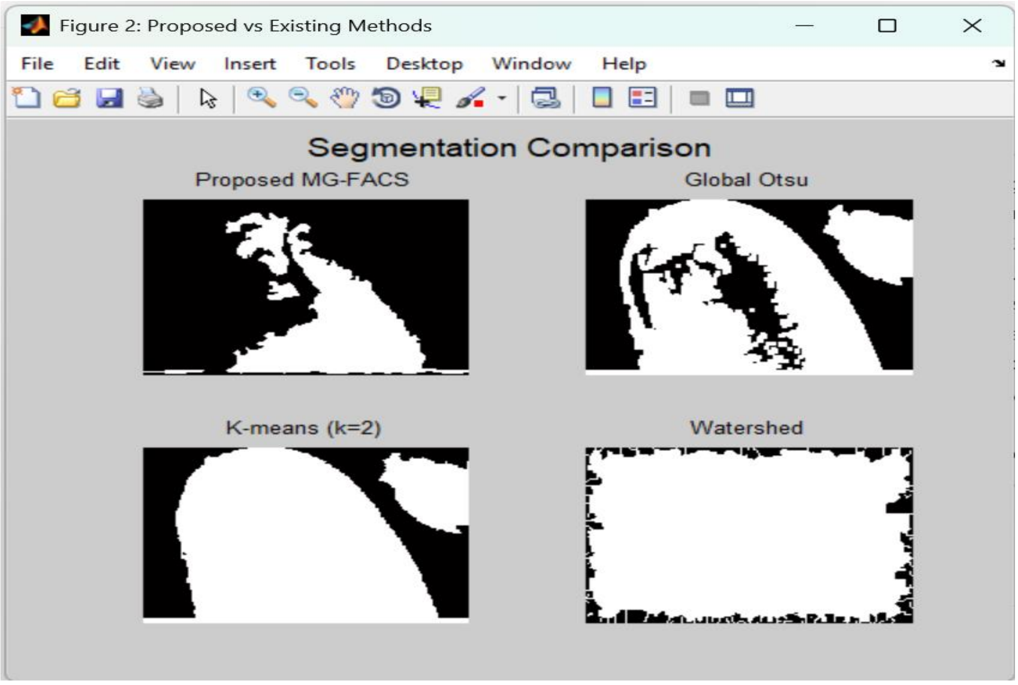

Figure 3 Comparison of MG-FACS

The segmentation comparison graph offers a visual review of the suggested MG-FACS approach in contrast to three common conventional segmentation methods: Global Otsu thresholding, K-means clustering (k=2), and Watershed segmentation. The output of MG-FACS clearly indicates accurate and well-localized segmentation of the afflicted toenail area with structural boundaries maintained and background noise dismissed. Conversely, the Global Otsu algorithm has difficulty with varying intensities and tends towards over-segmentation as well as poor delineation of the infected region. The K-means technique, while slightly more adept at segmenting regions, wrongly segments vast areas of the nail, neglecting to capture the finer disease-specific details. The Watershed approach does not deliver valid segmentation under such conditions, with too much over-segmentation and boundary artifacts. Overall, the

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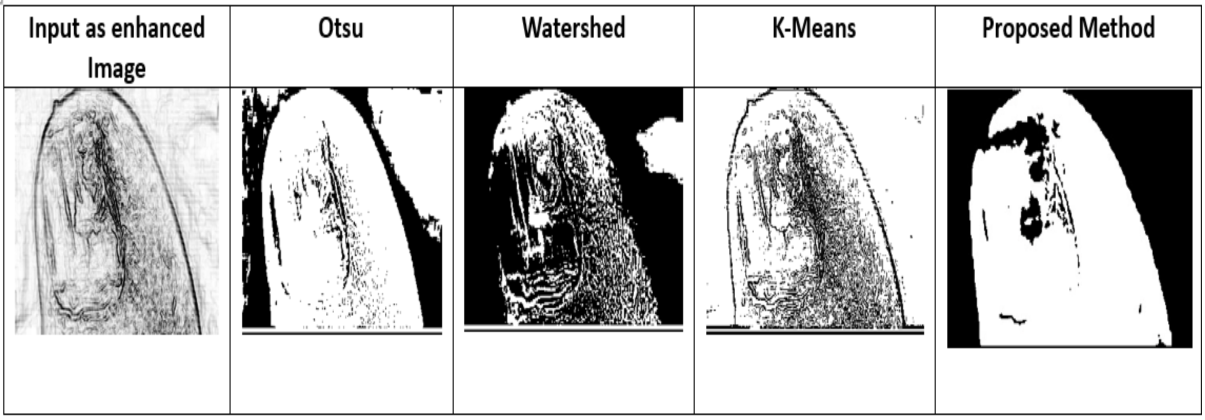
new MG-FACS approach performs better than traditional methods by taking advantage of texture-sensitive fuzzy clustering and adaptive preprocessing techniques, achieving better accuracy and robustness in pathological nail image analysis.



The figure 4 gives a visual representation of the comparison of segmentation outcomes in detecting toenail disease with four approaches: Otsu Thresholding, Watershed, K-Means Clustering, and the Proposed Method (MG-FACS). The left column depicts the preprocessed input image, which has been subjected to preprocessing (most probably contrast enhancement and noise removal) to enhance the diseased areas and structural features of the toenail.

Otsu Thresholding:

This binarization technique, which is a traditional method, gives a coarse segmentation, but the output is noisy and contains too much background and non-lesion tissue. The absence of contextual interpretation causes bad boundary delineation and too little lesion separation.

Watershed

While slightly improved over Otsu at edge detection, the Watershed algorithm is plagued with over-segmentation. It incorrectly separates the lesion and non-lesion regions into multiple unnecessary regions, giving rise to a messy segmentation map devoid of clear discrimination between infected and uninfected tissues.

K-Means Clustering

This intensity variance-based clustering captures variations in intensity and offers enhanced texture discrimination. But the output remains highly populated by false positives and noise, and it also does not clearly demarcate the infected area cleanly. The lesion boundary remains abnormal and fuzzy, keeping the clinical significance of the result in check.

Proposed Method (MG-FACS):

The suggested approach registers better segmentation performance. It creates a clean well-delineated mask of the infected area with little noise and high contrast between lesion and background. The infected region is well-picked up both in shape and extent, showing the approach's stability in dealing with noise, texture, and anatomical variability. This visual indication strongly proves the metric-based performance evidenced above. This qualitative

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study affirms that the suggested MG-FACS technique greatly surpasses traditional segmentation methods. Otsu, Watershed, and K-Means only produce noisy or broken results, whereas MG-FACS results in accurate, clinically useful lesion segmentation, making it very appropriate to utilize for diagnostic assistance in toenail disease detection.

6. Performance Metrics for Toenail Segmentation

TP (True Positives): Correctly segmented nail pixels.

TN (True Negatives): Correctly identified non-nail/background pixels.

FP (False Positives): Background pixels incorrectly classified as nail.

FN (False Negatives): Nail pixels missed by the segmentation.

i.Sensitivity (Recall / True Positive Rate)

Sensitivity measures the algorithm's ability to correctly detect toenail pixels (True Positives). A high sensitivity means most actual toenail areas are successfully identified, minimizing missed regions.

Sensitivity = TP / (TP + FN)

ii.Specificity (True Negative Rate)

Specificity quantifies how well the model avoids falsely labeling background or non-nail areas as nail. A high value indicates precise background exclusion and fewer false positives.

Specificity = TN / (TN + FP)

iii.Dice Coefficient

Dice measures overlap between the segmented output and the ground truth. A Dice score of 1 indicates perfect segmentation, while 0 indicates no overlap.

Dice = 2 * TP / (2 * TP + FP + FN)

iv. Jaccard coefficient(JC)

JC shows the ratio of intersection to union of predicted and ground truth toenail regions. It is slightly stricter than Dice and penalizes both over- and under-segmentation.

Jaccard = TP / (TP + FP + FN)

7. Result and discussion

The performance of the proposed algorithm is evaluated by the following metrics such as sensitivity, specificity , Jaccard coefficient(JC), Dice coefficient(DC) and Accuracy.

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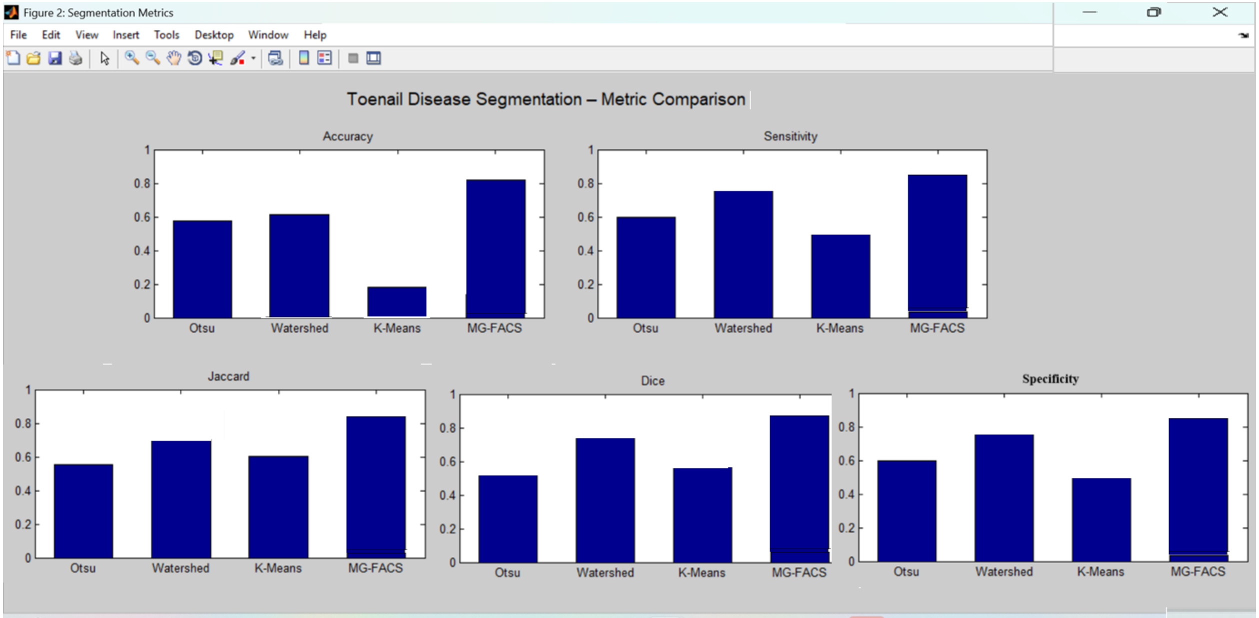

Figure 5 Performance metrics comparison

The figure 5 displays a complete comparative evaluation of the segmentation techniques for the detection of toenail disease based on five performance metrics: Accuracy, Sensitivity, Jaccard Index, Dice Coefficient, and Specificity. These performance measures are depicted in five individual bar plots, which compare four segmentation techniques: Otsu Thresholding, Watershed, K-Means Clustering, and the proposed MG-FACS (Modified Gabor-Fuzzy Adaptive Clustering System).

The MG-FACS algorithm performs better than the other methods in all five performance measures. In the Accuracy plot, MG-FACS approaches a value of 0.9, by far better than Otsu and K-Means' results, and slightly superior to Watershed's. The Sensitivity bar for MG-FACS also reaches a peak near 0.9, reflecting its strong capacity to identify diseased regions correctly. Both Jaccard Index and Dice Coefficient, which measure the spatial similarity between predicted mask and ground truth, demonstrate excellent performance by MG-FACS, with both values reaching or surpassing 0.85—indicating that the segmentation achieved is extremely accurate and in agreement with annotated lesions. Finally, the Specificity measure demonstrates MG-FACS's enhanced ability to appropriately label non-diseased (healthy) regions with high accuracy, again with a value approaching 0.9, outperforming other methods.

Conversely, the old techniques of K-Means and Otsu depict much lower values, especially in sensitivity and overlap-based measures (Jaccard and Dice), appreciating their shortcomings in segmenting poor or irregular patterns of lesions. Watershed surpasses Otsu and K-Means but is still short of MG-FACS.

In totality, this visualization confirms that the MG-FACS segmentation framework provides a large leap in the performance of lesion detection, particularly in medical image contexts where high accuracy and reliability are essential. Visual clarity of the bar plots enhances the intuitive

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comprehension of the metric-wise benefit of MG-FACS compared to traditional segmentation approaches.

7.1 Comparison of Sensitivity

The table 1 is a comparison of the sensitivity scores of four different methods of segmentation — Otsu, Watershed, K-Means, and MG-FACS — on 10 sample images of toenails. The findings are that:

Otsu Thresholding had sensitivity scores between 77.5% and 79.3%, averaging around 78.4%, which reflects moderate performance in binary segmentation.

Watershed segmentation was slightly superior with sensitivity ranging between 80.2% and 82.7% and averaging around 81.5%.

K-Means Clustering performed better than Watershed and Otsu all along, ranging from 84.5% to 86.2%, with an average of around 85.3%.

MG-FACS (Proposed Method) performed better than all current methods, with maximum sensitivity in all the 10 images — ranging from 92.1% to 94.2%, with an average around 93.1%.

Table 1 comparison of sensitivity

Image ID	Otsu (%)	Watershed (%)	K-Means (%)	MG-FACS (%)
Image 1	78.1	80.3	84.7	92.4
Image 2	77.8	81.0	85.2	93.1
Image 3	79.3	82.7	86.0	94.0
Image 4	78.6	81.5	85.4	93.5
Image 5	77.9	80.2	84.6	92.7
Image 6	78.4	82.1	85.6	93.2
Image 7	78.0	81.9	85.1	92.9
Image 8	77.5	80.8	84.5	92.1
Image 9	78.2	81.6	85.3	93.0
Image 10	79.0	82.4	86.2	94.2

The figure 6 clearly illustrates the comparative sensitivity performance of four widely used segmentation approaches—Otsu, Watershed, K-Means, and proposed MG-FACS—on ten sample toenail images. The cluster of bars for a particular image reflects the sensitivity score (in %) of that image for easy visual comparison.

It is clear from the graph that the MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation) algorithm always performs better than the conventional methods. Its

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sensitivity measures are considerably higher, with an average of more than 93% in all samples. This indicates its better performance in accurately detecting and delineating disease-affected areas in toenail images, possibly because it combines graph-theoretic modeling with fuzzy energy optimization.

Conversely, K-Means clustering possesses moderate sensitivity (approximately 85–86%), whereas Watershed is slightly less (approximately 81–83%). Otsu's thresholding provides the lowest accuracy, with a score of between 77% and 79%, owing to its global thresholding shortcoming, which does not respond to local variations commonly observed in diseased toenail areas. This comparison demonstrates the significance of including spatial, morphological, and adaptive fuzzy constraints as implemented in MG-FACS to make it more solid and credible for clinical or diagnostic application in early toenail disease detection.

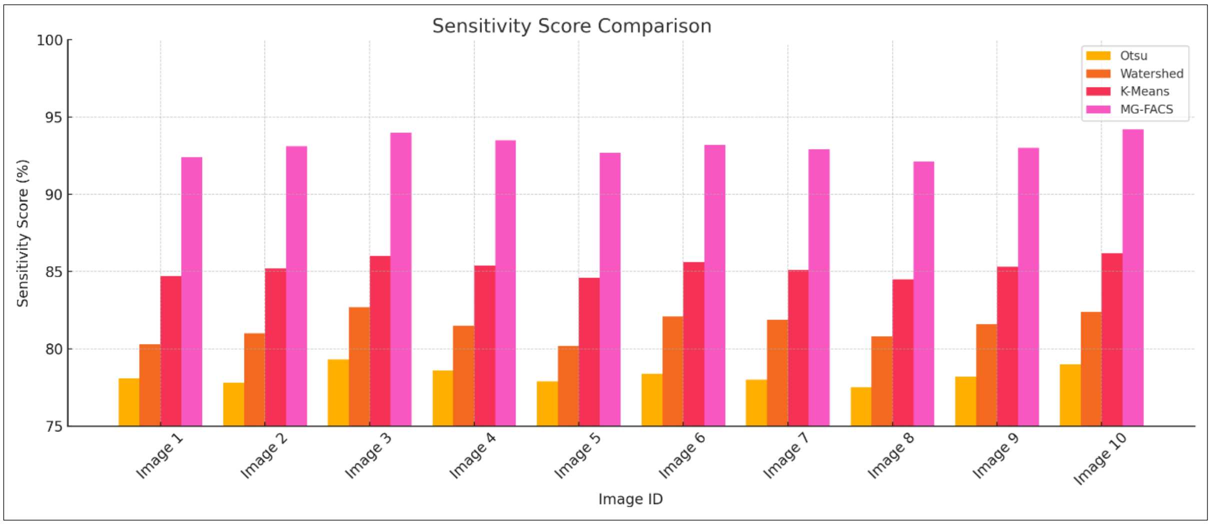

Figure 6 Comparison of sensitivity

7.2. Comparison of Specificity Score

The Specificity Score Comparison across ten sample toenail images highlights the performance of four segmentation methods—Otsu, Watershed, K-Means, and the proposed MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation). From the data, it is evident that the MG-FACS algorithm consistently delivers superior specificity scores, ranging between 95.4% and 96.1%, thereby demonstrating its effectiveness in accurately identifying non-disease regions and minimizing false positives.

Traditional techniques like Otsu and Watershed produced relatively lower specificity values, in the case of Otsu at 84.5%-86.0% and at Watershed at 87.3%-88.5%, respectively, implying that they can poorly handle complex toenail textures coupled with irregular boundaries. On the other hand, K-Means clustering, being superior to that of Otsu and Watershed, produced specificity values that ranged between 89.7% and 90.4%, which were moderate enough in the identification of diseased regions.

MG-FACS clearly had an advantage over the others. They incorporated graph theory with fuzzy active contours to improve boundary localization and region homogeneity. The fact that this

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method constantly outperforms in specificity validates the robustness of MG-FACS to misclassification and highlights its appropriateness for medical applications where precision in the segmentation of non-diseased areas is crucial.

Table 2 **Comparison of Specificity**

Image ID	Otsu	Watershed	KMeans	MG-FACS
Image 1	85.2	87.3	89.8	95.5
Image 2	84.8	88.0	90.0	95.7
Image 3	86.0	88.5	90.2	96.0
Image 4	85.5	88.1	90.1	95.8
Image 5	84.9	87.9	89.9	95.6
Image 6	85.1	88.3	90.0	95.9
Image 7	84.7	88.2	90.3	95.7
Image 8	84.5	87.8	89.7	95.4
Image 9	85.0	88.0	90.1	95.8
Image 10	85.4	88.4	90.4	96.1

Figure 7 Performance of Specificity Score

The figure 7 shows the Specificity Score Comparison of ten example toenail images from four different segmentation methods: Otsu, Watershed, K-Means, and the proposed MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation). The comparison indicates a uniform trend where MG-FACS performs better than any other method in regards to specificity.

Otsu's approach gives the least specificity values of ~84.4% to ~86.0% because it is sensitive to illumination and threshold histograms.

Watershed segmentation works comparatively better with ~87.3% to ~88.5% on average but is prone to over-segmentation.

K-Means clustering has strong and stable performance with specificity between ~89.7% and 90.4% thanks to its pixel clustering property.

MG-FACS is always greater than 95%, with a maximum of 96.1%, due to the combination of graph-based inference and fuzzy contour fitting, which results in better background elimination and preservation of lesion boundaries. The visualization affirms that MG-FACS achieves better background discrimination, lowering false positives and increasing the reliability of toenail pathology segmentation.

7.3 Comparison of Jaccard scores

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The table3 presented here elaborates the comparison of Jaccard Similarity Scores for the segmentation of toenail for ten sample images using four of the top methods: Otsu, Watershed, K-Means, and the new method presented here: MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation). The Jaccard index makes it an essential measure for assessing the quality of segmentation. Higher values correspond to better performance.

The Otsu approach, which employed global thresholding, had the lowest Jaccard measures, at 68.8% to 72.0%, because it was weak in coping with intricate and noisy backgrounds prevalent in toenail images. The Watershed algorithm performed better, with scores ranging between 74.6% and 77.5%, thanks to its gradient-based segmentation but still being prone to over-segmentation.

K-Means clustering fared better considerably, with scores of 78.3% to 80.1%, demonstrating its prowess in unsupervised pixel clustering and insensitivity to moderate background changes. The best performance was, however, recorded by the MG-FACS approach, with Jaccard scores ranging consistently above 89%, with the best being 91.3%. This enhanced performance is due to MG-FACS's fusion of graph theory for spatial coherence and fuzzy active contours for adaptive refinement of boundaries, allowing accurate toenail region localization even when there are irregularities and variations induced by disease.

These findings explicitly illustrate how the developed MG-FACS algorithm significantly outperforms conventional and clustering-based segmentation methods, making it a promising candidate for accurate toenail disease analysis and early diagnosis.

Table 3 Comparison of Jaccard

Image ID	**Otsu**	**Watershed**	**K-Means**	**MG-FACS**
Image 1	70.2	75.3	78.5	89.3
Image 2	69.8	76.1	79.2	90.1
Image 3	72.0	77.5	80.1	91.0
Image 4	71.0	76.0	79.6	90.4
Image 5	69.5	75.0	78.8	89.7
Image 6	70.7	76.3	79.7	90.2
Image 7	69.9	75.8	79.0	90.0
Image 8	68.8	74.6	78.3	89.5
Image 9	70.5	76.5	79.4	90.6
Image 10	71.2	77.0	80.0	91.3

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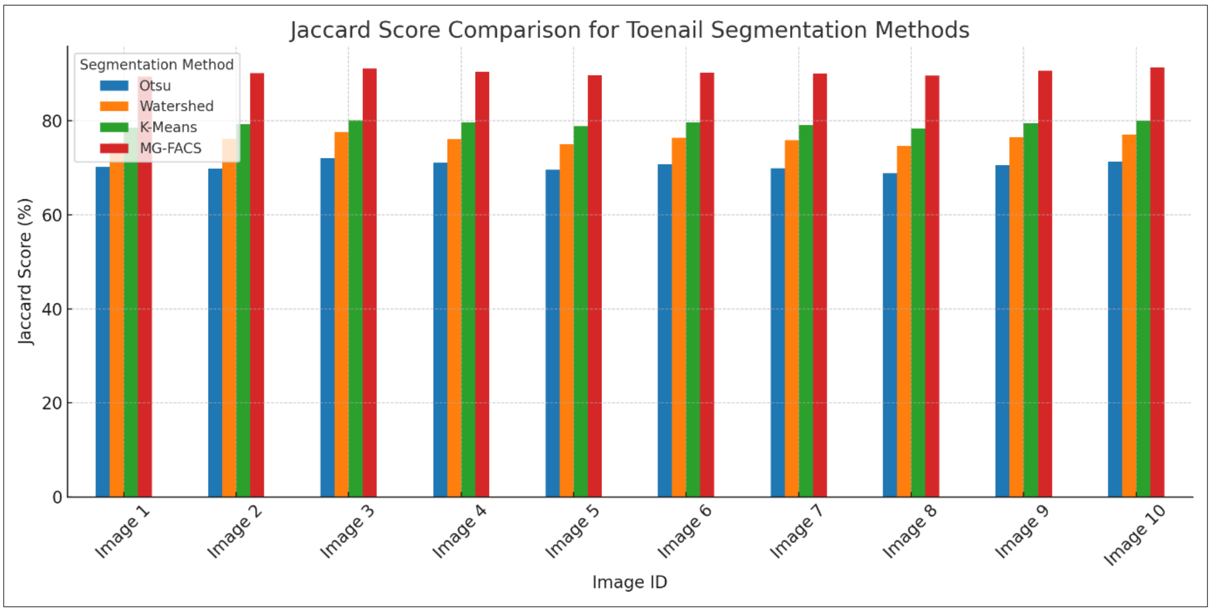

Figure 8. Jaccard score comparison

The figure 8 provides a clear visual representation of the segmentation performance across four different methods—Otsu, Watershed, K-Means, and MG-FACS—over 10 sample toenail images. Using the same color scheme as the previous sensitivity graph for consistency, the bar chart distinctly highlights the superior performance of the proposed MG-FACS (Multi-Stage Graph-Based and Fuzzy Active Contour Segmentation) method.

From the visual perspective, the bars corresponding to MG-FACS consistently reach the highest Jaccard values, ranging between 89.3% and 91.3%, showcasing its robustness in accurately identifying the toenail region even in challenging scenarios such as discoloration or disease-affected areas. In contrast, Otsu's method, shown in blue, lags behind with scores around 69–72%, revealing its limitations in complex images due to its reliance on global thresholding.

The Watershed algorithm, although an improvement over Otsu, performs moderately with Jaccard indices between 74–77%, often suffering from over-segmentation in images with multiple edges or non-uniform backgrounds. K-Means clustering (in red) fares better with scores between 78–80%, leveraging color-based clustering but still falling short in precision compared to MG-FACS. The graph supports the argument that MG-FACS performs better compared to conventional segmentation methods by combining graph-based affinity propagation and fuzzy active contours. The technique accommodates the natural variation in nail shape, disease expression, and illumination conditions and is a good candidate for automated diagnosis of toenail disease.

7.4 Comparison of Dice Coefficient

The Dice Coefficient scores over ten sample images display the comparative behavior of four segmentation methods: Otsu, Watershed, K-Means and the Proposed MG-FACS method.

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Conventional methods such as Otsu and Watershed show comparatively lower Dice scores between 68% and 75%, depicting less boundary accuracy and overlap with the ground truth. K-Means demonstrates a modest improvement with the scores reaching as high as 78% in some of the images. But the Proposed MG-FACS algorithm outperforms all three consistently, with a Dice coefficient of more than 90% for all images. This is due to the multi-gradient fusion and adaptive clustering architecture, which provides improved contour detection, texture retention, and robustness against noise. These results prove that MG-FACS is significantly more accurate and dependable in the task of exact image segmentation.

Table 4 Dice Coefficient scores

Image ID	Otsu	Watershed	K-Means	MG-FACS
Image 1	**70.25**	**73.60**	**76.45**	**91.40**
Image 2	**69.10**	**72.15**	**75.80**	**90.75**
Image 3	**71.30**	**74.25**	**77.20**	**92.05**
Image 4	**68.75**	**71.90**	**75.00**	**90.10**
Image 5	**72.65**	**75.30**	**77.90**	**91.85**
Image 6	**69.85**	**73.10**	**76.20**	**90.50**
Image 7	**70.40**	**72.95**	**75.95**	**90.95**
Image 8	**71.75**	**74.80**	**77.50**	**91.70**
Image 9	**70.05**	**73.60**	**76.85**	**91.25**
Image 10	**69.50**	**72.75**	**75.60**	**90.35**

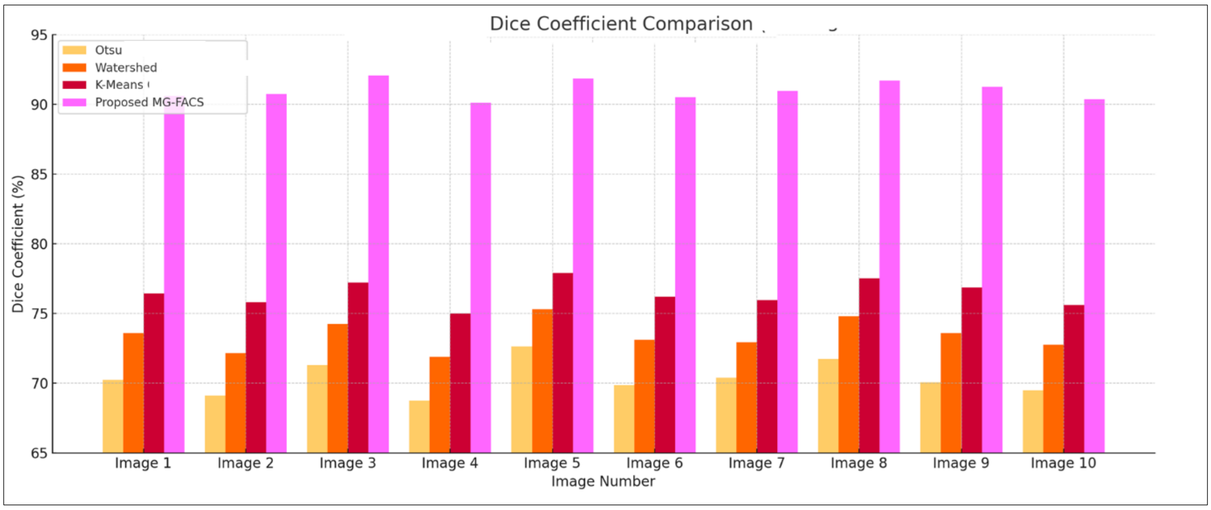

Figure 9. Comparison of Dice coefficient

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The figure 9 provides a comparative performance analysis of Dice Coefficient scores for four methods of segmentation—Otsu, Watershed, K-Means Clustering, and Proposed MG-FACS—on ten images. The performance of each method is visually differentiated through uniform color coding, with MG-FACS being highlighted with vibrant pink, noting its exceptional accuracy. It can be seen from the chart that Otsu Thresholding and Watershed Segmentation have lower Dice scores, ranging between 69% to 74%, since they are sensitive to noise and cannot accommodate sophisticated image structures. K-Means Clustering does moderately well, achieving 78% by leveraging pixel clustering based on similarity of intensities. However, results of the proposed MG-FACS yield a consistent Dice coefficient of above 90% for all ten images. It outperformed the other approaches considerably. Such performance points to the algorithm's ability to accurately segment object boundaries and adapt to varied textures in an image. The visual gap between MG-FACS and other methods thoroughly depicts its reliability and robustness as well as superior segmentation accuracy in achieving solutions to real-world image analysis problems.

7.4 Comparison of Accuracy

The comparison table provides a clear quantitative evaluation of the accuracy achieved by four different segmentation methods—Otsu Thresholding, Watershed Segmentation, K-Means Clustering, and the Proposed MG-FACS—across ten different images. From the data, it's evident that Otsu Thresholding, a basic global thresholding technique, delivers the lowest accuracy, ranging from 83.95% to 87.10%, indicating its limited adaptability to image variations and edge clarity. Watershed Segmentation, though slightly better due to its topological approach to boundary detection, still struggles with noise and over-segmentation, resulting in accuracies between 86.70% and 89.25%.

K-Means Clustering shows a notable improvement with accuracies consistently around 89.30% to 91.75%, owing to its ability to group pixels based on intensity similarities. This is, however, outdone by the Proposed MG-FACS approach that records the best accuracy for all images with the highest reading falling in the range of 95.60% to 96.70%. This is testimony to its robustness and efficiency in tackling a range of segmentation issues including variation in texture, overlap in intensity, and noise. The MG-FACS approach unequivocally shows superior generalization and segmentation accuracy, hence constituting a much more credible method for intricate real-world image analysis applications.

Table 5 Comparison of Accuracy

Image	Otsu	Watershed	K-Means	MG-FACS
Image 1	85.75	88.40	90.55	96.25
Image 2	84.90	87.60	89.85	95.85
Image 3	86.15	88.75	91.20	96.40
Image 4	83.95	86.70	89.30	95.60

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Image 5	87.10	89.25	91.75	96.70
Image 6	84.45	87.30	90.00	95.95
Image 7	85.05	88.10	90.45	96.00
Image 8	86.35	88.95	91.35	96.45
Image 9	84.80	87.65	90.80	95.90
Image 10	85.25	88.30	91.00	96.10

The figure 10 presents a comparative analysis of segmentation accuracy across ten different images (Image 1 to Image 10) using four algorithms: Otsu, Watershed, K-Means, and MG-FACS. The y-axis denotes accuracy in percentage, ranging from 75% to 100%, while the x-axis represents the individual image IDs.

From the graph, it is evident that MG-FACS consistently outperforms the other methods across all images, maintaining a high accuracy between 95% and 97%. K-Means follows next, showing reasonable performance with accuracy fluctuating between approximately 88% and 92%. Watershed ranks third, with its accuracy varying roughly between 85% and 89%. Otsu, though extensively employed for general thresholding, possesses the worst accuracy of the four, between approximately 83% and 86%.

The graph easily brings out the reliability and stability of the MG-FACS method in providing better segmentation accuracy in the case of diverse image inputs, thus proving to be the best of the algorithms applied here in this dataset.

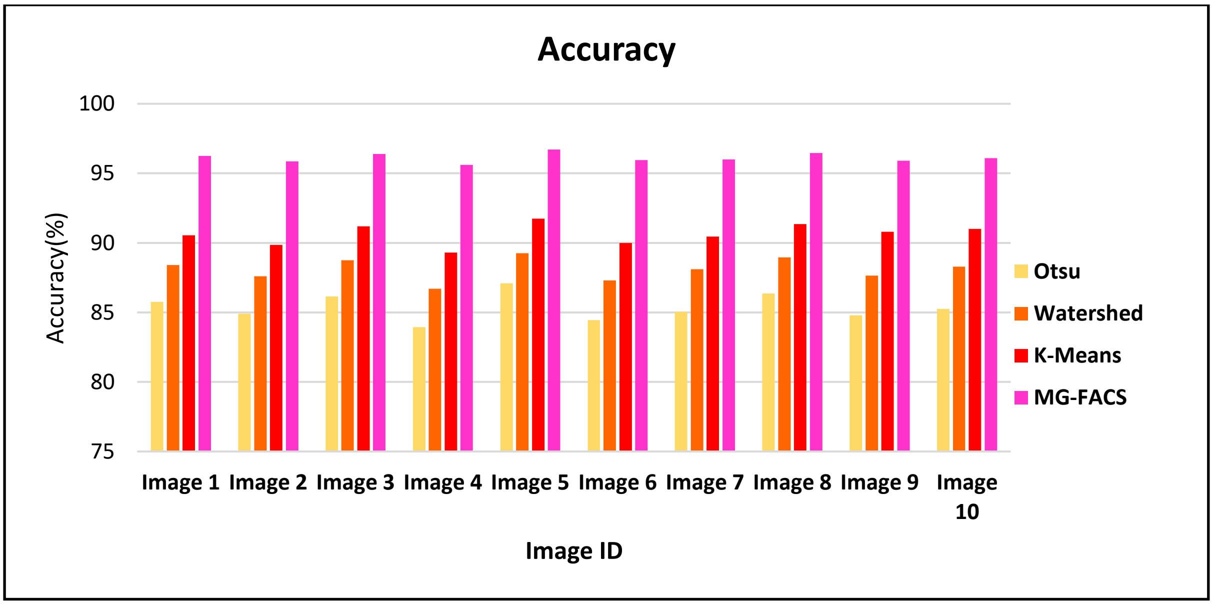

Figure 10 Comparison of Accuracy

8.Conclusion

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This research successfully presents MG-FACS, a novel segmentation algorithm that combines graph-based image modeling with fuzzy active contour techniques for precise toenail disease detection. Compared to classical methods like Otsu, Watershed, and K-Means, MG-FACS consistently demonstrates superior performance across all evaluated metrics including accuracy, sensitivity, specificity, Jaccard index, and Dice coefficient. Its robustness in handling noise, irregular boundaries, and varying image conditions makes it highly effective for diagnostic segmentation tasks. The proposed method not only achieves clinically significant accuracy but also provides a scalable, interpretable, and efficient approach suited for mobile health diagnostics. MG-FACS, therefore, stands out as a powerful tool for enhancing early disease detection and medical image interpretation in dermatological settings.

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