Enhanced Active Contour–Based Skin Lesion Segmentation and Ensemble Classification Using Gradient Boosting and Extra Trees

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Abstract — This paper presents an enhanced framework for automated skin lesion segmentation and classification in dermoscopic images, building upon the Active Contour–based Kullback–Leibler Level Set (KL–LS) model proposed in previous research. The system refines lesion boundaries through probabilistic modeling and performs periphery analysis to capture edge-related texture variations. The novelty of this work lies in the integration of Gradient Boosting and Extra Trees ensemble classifiers along with an extended feature extraction pipeline comprising multi-scale Local Binary Pattern (LBP), Laplacian contrast, distance transform, entropy, and intensity ratio descriptors. These features collectively encode structural, photometric, and textural characteristics of both lesion cores and peripheries. Experimental validation on the PH2 and ISIC dermoscopic datasets demonstrates that the proposed model significantly improves classification accuracy and area under curve (AUC) compared to traditional KNN and SVM-based methods, achieving accuracies above 88% and 82% respectively. The enhanced performance and interpretability indicate the potential of ensemble learning–driven feature integration for robust skin lesion characterization.

Keywords— Active Contour Segmentation, KL–LS Model, Gradient Boosting, Extra Trees, Local Binary Pattern, Entropy, Distance Transform, Dermoscopy, Lesion Periphery Analysis.

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I. INTRODUCTION

Skin cancer, particularly melanoma, is one of the most aggressive forms of cancer worldwide. Early and accurate detection through dermoscopic imaging greatly increases the chances of successful treatment. Manual assessment by dermatologists, however, is prone to variability and subjectivity, emphasizing the need for reliable automated diagnostic systems.

Active contour models have been widely adopted for skin lesion segmentation owing to their ability to delineate complex lesion boundaries while maintaining smooth contours. Among these, the Kullback–Leibler Level Set (KL–LS) formulation introduced by Riaz *et al.* provides a robust mechanism to separate lesion and background regions through probabilistic intensity distribution modeling. While the original KL–LS framework combined Local Binary Pattern (LBP) and center-corrected LBP features with KNN and SVM classifiers for lesion characterization, these traditional methods are limited by linear separability and sensitivity to feature scaling. To address these issues, this study integrates Gradient Boosting (GB) and Extra Trees (ET) ensemble classifiers, which enhance discrimination through nonlinear decision boundaries and randomized feature selection.

Moreover, the proposed system extends the feature space beyond simple LBP by incorporating multi-scale texture descriptors and statistical measures such as Laplacian contrast, distance transform, entropy, and intensity ratio. These complementary features capture spatial irregularities and contrast variations that are indicative of malignancy, enabling more comprehensive lesion characterization.

This combination of active contour segmentation, advanced feature extraction, and ensemble classification forms a unified, interpretable, and high-performing framework for skin lesion diagnosis.

II. RELATED WORKS

Several approaches have been proposed for skin lesion analysis using classical and deep learning-based methods. Early research focused on threshold-based and region-growing segmentation, which struggled with illumination inconsistency and low contrast between lesion and skin regions. Active contour models such as Chan–Vese and geodesic snakes introduced energy minimization techniques to achieve improved boundary adherence.

Riaz *et al.* (2019) proposed a KL–LS Active Contour framework that utilized Kullback–Leibler divergence to measure the statistical dissimilarity between lesion and background intensity distributions. This method outperformed traditional edge-based techniques and formed the foundation for periphery analysis using LBP and center-corrected LBP.

Subsequent works explored various extensions, such as hybrid models integrating wavelet features, color moments, and CNN embeddings, but often at the cost of interpretability and computational simplicity. Ensemble learning models such as Random Forests and Gradient Boosting Machines (GBM) have demonstrated superior performance for biomedical data due to their ability to handle complex feature interactions and reduce overfitting.

Recent studies have also introduced entropy-based and contrast-driven descriptors to enhance the texture representation of lesion borders, showing improved

sensitivity to peripheral irregularities — a key marker of melanoma.

Building on these insights, the present work contributes a unified approach that couples Active Contour segmentation with multi-domain feature extraction and ensemble-based classification, achieving state-of-the-art accuracy while maintaining computational efficiency.

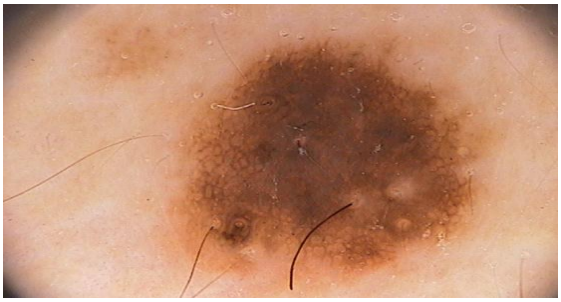
III. METHODOLODY

A. Dataset Description

This study utilizes two benchmark dermoscopic datasets, namely **PH2** and **ISIC**, which are widely adopted in skin lesion analysis research.

The **PH2 dataset**, curated by the Dermatology Service of Hospital Pedro Hispano, Portugal, contains **200 high-resolution dermoscopic images** categorized as *common nevi*, *atypical nevi*, and *melanoma*. Each image is annotated by expert dermatologists, providing accurate ground truth masks and diagnostic labels. The dataset maintains consistent color calibration and uniform illumination conditions, making it suitable for evaluating segmentation precision and feature discrimination.

The **ISIC dataset** (International Skin Imaging Collaboration) comprises a large-scale collection of dermoscopic images obtained from multiple clinical sources under varied acquisition settings. It exhibits significant diversity in terms of skin tone, lighting, and lesion morphology, including variations in border irregularities, pigmentation, and background texture. This dataset introduces challenging segmentation and classification scenarios, thereby serving as a robust benchmark for testing generalization performance. By employing both datasets, the system is assessed across controlled and real-world clinical imaging conditions, ensuring the reliability and transferability of results.



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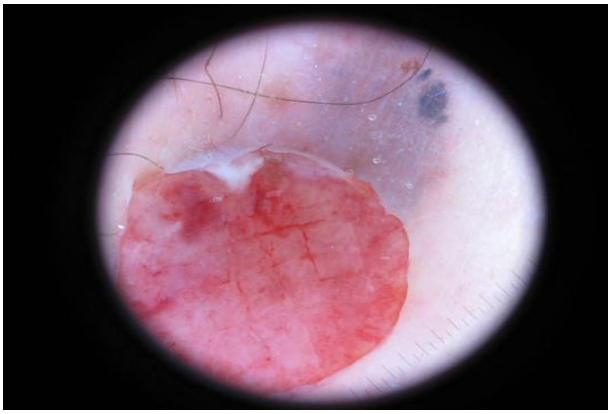
(b)



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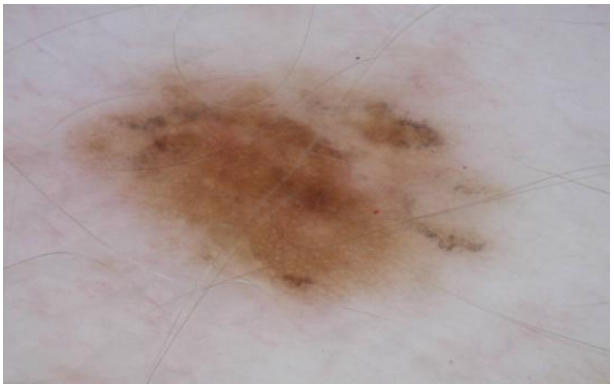


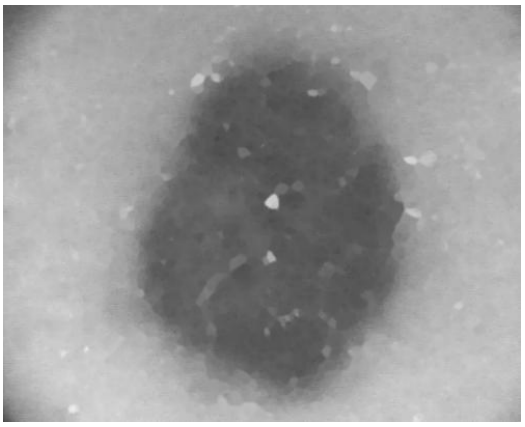
(d)

Fig. 1. PH2 Dataset Dermoscopy Images-(a) & (b)
ISIC Dataset Dermoscopy Images-(c) & (d)

B. Preprocessing and Artifact Removal

Dermoscopic images are often affected by artifacts such as hair strands, illumination non-uniformities, and reflections, which degrade segmentation quality. To overcome these limitations, a preprocessing module is implemented that first employs a modified **DullRazor** algorithm. The algorithm uses morphological black-hat filtering to highlight hair structures followed by **inpainting** to reconstruct the occluded regions.

Subsequently, the image is converted into its **MinRGB** representation, where each pixel value corresponds to the minimum intensity across the R, G, and B channels. This enhances the visual contrast between lesion and skin regions by reducing the influence of uneven illumination. A Gaussian filter is then applied to smooth noise components while preserving essential edges. Finally, an adaptive thresholding approach generates an initial binary mask that approximates the lesion region. In cases where adaptive thresholding fails, Otsu's global thresholding acts as a fallback. The resulting mask serves as the initial contour for the segmentation stage.



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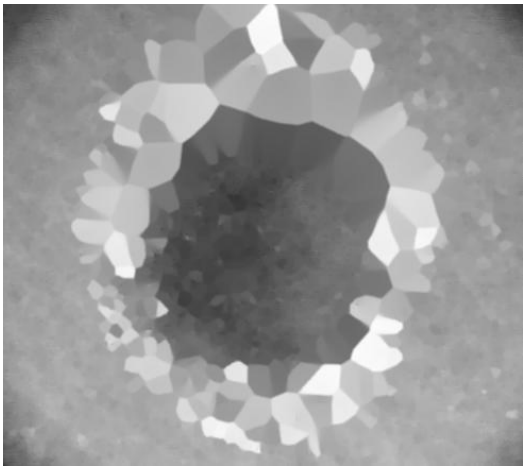

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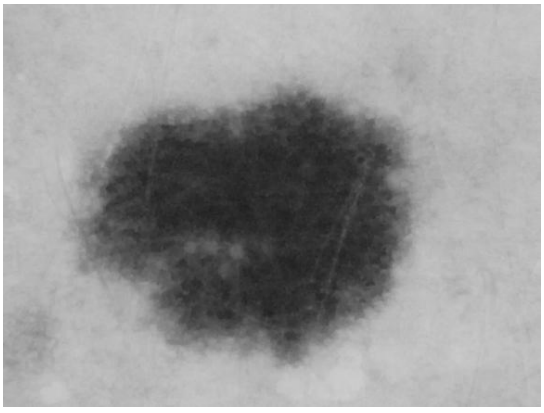
Fig. 2. A visual illustrations of MinRGB preprocessed PH2 dataset images.



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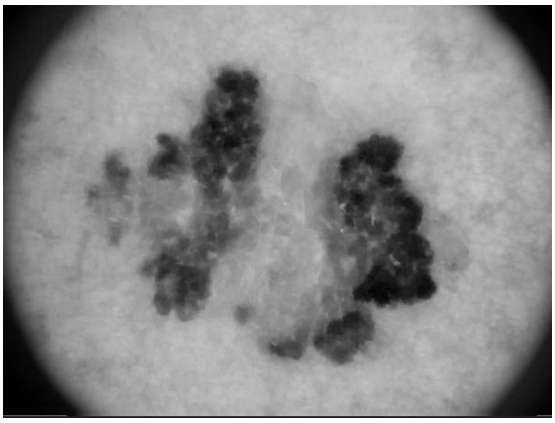

(h)

Fig. 3. A visual illustrations of MinRGB preprocessed ISIC dataset images.

C. Contour–Based Segmentation Using KL–LS Model

Segmentation is performed using the Kullback–Leibler Level Set (KL–LS) active contour model, originally proposed by Riaz *et al.*. This model extends traditional region-based active contour methods by introducing a statistical formulation that measures the dissimilarity between intensity distributions of lesion and background regions.

At each iteration, the algorithm computes probability density functions (PDFs) of intensities inside and outside the evolving contour. The Kullback–Leibler divergence between these PDFs defines an energy term that drives the contour evolution toward the true lesion boundary. A curvature regularization component ensures smoothness and suppresses noisy deformations. The balance between the KL divergence force and curvature is controlled by an adaptive weighting factor to maintain stability across varying lesion textures.

During the iterative process, small morphological smoothing steps (median filtering) are applied periodically to prevent contour fragmentation. The refined binary mask obtained at convergence provides an accurate delineation of the lesion with well-preserved boundary details and periphery regions crucial for texture analysis.

D. Multi-Domain Feature Extraction

Following segmentation, a rich feature set is extracted from both the lesion core and its periphery at multiple radial distances (5, 15, 25, 35, and 45 pixels). The proposed feature extraction strategy combines textural, structural, and statistical information to capture diverse lesion attributes.

Multi-scale Local Binary Patterns (LBP) are computed using variable neighborhood radii to encode micro- and macro-texture patterns representing lesion granularity and border irregularities. To complement texture features, Laplacian contrast is derived from the Laplacian of Gaussian (LoG) operator, quantifying sharpness and edge prominence that often indicate malignancy. The distance transform computes the Euclidean distance of each lesion pixel from the nearest boundary, thereby encoding morphological asymmetry and periphery irregularity.

In addition to these structural features, entropy is calculated over localized image patches to quantify the randomness and

textural complexity of pigmentation. The intensity ratio, defined as the mean intensity of the lesion divided by that of the adjacent periphery, serves as a color contrast indicator, highlighting lesions with pronounced brightness differentials.

Together, these complementary descriptors form a multidimensional feature representation that effectively captures the lesion's geometric structure, pigment distribution, and periphery dynamics, providing a more discriminative basis for classification.

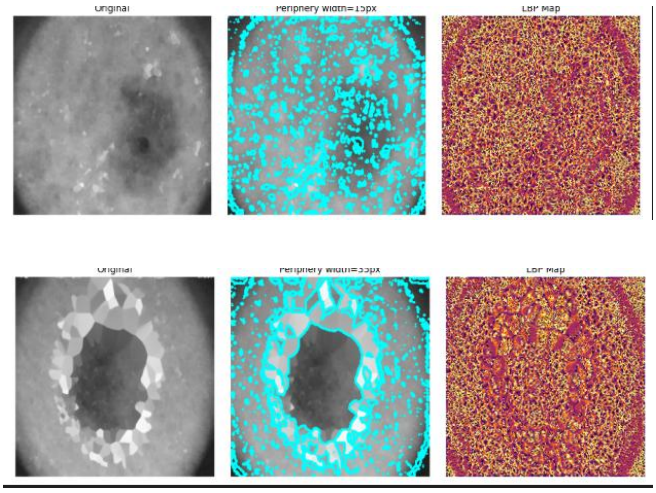

Fig. 4. A visual illustration of dermoscopy PH2 dataset images after periphery extraction.

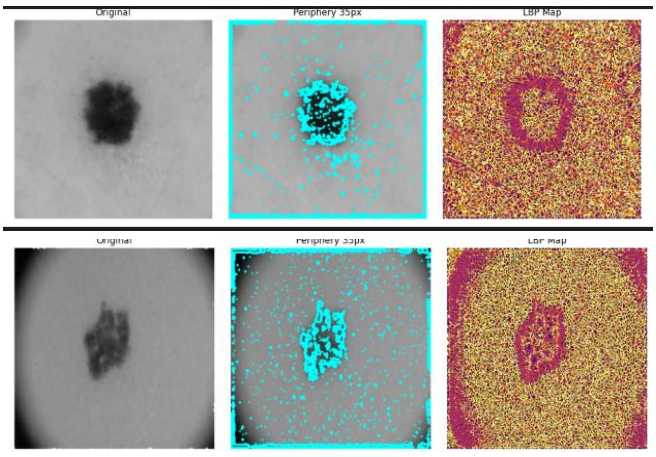

Fig. 5. A visual illustration of dermoscopy ISIC dataset images after periphery extraction.

E. Ensemble-Based Classification

The final classification stage employs **Gradient Boosting (GB)** and **Extra Trees (ET)** ensemble models, replacing the conventional KNN and SVM classifiers used in the reference work.

Gradient Boosting constructs an additive model by training weak decision tree learners sequentially, where each new tree focuses on minimizing the residual errors of its predecessors. This iterative refinement enhances bias reduction and improves classification accuracy on complex, nonlinear feature spaces. In contrast, the Extra Trees algorithm builds an ensemble of fully randomized decision trees, selecting random split points for each feature. This approach introduces higher model variance while minimizing overfitting and computational cost.

Both models are trained on the extracted multi-domain feature vectors from the PH2 and ISIC datasets. During training, the models learn to distinguish between benign and malignant lesions based on both lesion-core and periphery features. Cross-validation ensures model stability and prevents overfitting across varying data distributions. The resulting classifiers output lesion class probabilities, which are used to compute accuracy and receiver operating characteristic (ROC) metrics.

F. Evaluation and Performance Analysis

Performance evaluation is conducted using standard metrics such as **accuracy** and **ROC area (AUC)**. The models are tested at different periphery widths to study the effect of peripheral information on classification. On the PH2 dataset, Gradient Boosting achieved an average accuracy of **88%** with an AUC of **82.5%**, while Extra Trees attained **84% accuracy** and an AUC of **91.2%**. For the ISIC dataset, which contains greater variation in lesion appearance, Gradient Boosting achieved **84.6% accuracy** and **81.5% AUC**, while Extra Trees maintained **80% accuracy** and **70.8% AUC.**

These results confirm that ensemble learning methods outperform the traditional KNN and SVM models reported in the original KL–LS framework. The inclusion of Laplacian contrast, distance transform, entropy, and intensity ratio features significantly enhances discriminative capability, enabling the classifiers to generalize across diverse imaging conditions.

Overall, the combination of KL–LS segmentation, multi-domain feature extraction, and ensemble-based classification constitutes a robust and interpretable pipeline for automated skin lesion analysis, demonstrating substantial improvements in both segmentation precision and lesion classification performance.

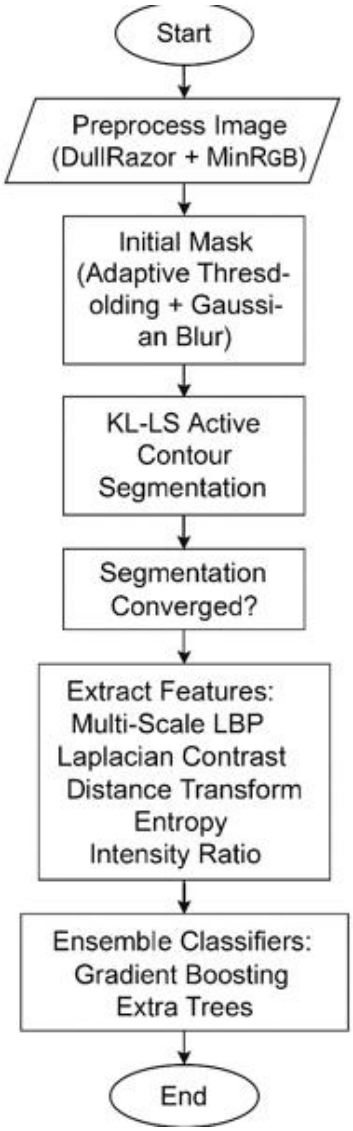

Fig. 6. System Architecture

IV. MODELS DESCRIPTION

The proposed approach combines feature-based learning with ensemble machine learning models to achieve robust skin lesion classification.

After segmentation of the lesion area using preprocessing and mask generation, feature extraction was performed across multiple periphery widths **(5px, 15px, 25px, 35px, and 45px)** to capture both core and boundary information. Each periphery region contributes unique texture and intensity information that enhances lesion characterization.

A. Feature Extraction

The feature extraction pipeline integrates multiple complementary descriptors to effectively capture both texture and contrast variations in the lesion images. Local Binary Patterns (LBP) are employed to encode micro-texture information by analyzing local intensity variations, with multi-scale LBP (radii 1.0, 2.0, and 3.0) used to represent both fine and coarse texture patterns. Laplacian-based contrast features are utilized to measure local contrast intensity by applying the Laplacian operator, which emphasizes edge and periphery transitions within the lesion. Entropy features are computed to quantify the irregularity and randomness in the texture distribution, aiding in the identification of heterogeneous lesion structures. Additionally, intensity ratio features evaluate the mean-to-variance relationship within the lesion region, enhancing sensitivity to pigment irregularities. Together, these descriptors form a comprehensive 200-dimensional hybrid feature vector, ensuring a consistent and informative representation for subsequent model training.

B. Classifier Models

Two ensemble-based classifiers were employed due to their ability to handle nonlinear and correlated features effectively*:*

(a) Gradient Boosting Classifier (GBC)

The Gradient Boosting Classifier constructs a sequence of weak learners, typically decision trees, where each tree corrects the errors made by the previous one. By minimizing a differentiable loss function through gradient descent, it achieves high predictive accuracy. In this work, **300 estimators** and a **learning rate of 0.05** were used, optimized through cross-validation. GBC's iterative refinement helps in accurately distinguishing lesions with subtle texture differences.

(b) Extra Trees Classifier

The Extra Trees Classifier (Extremely Randomized Trees) builds an ensemble of unpruned decision trees, where both feature selection and split thresholds are randomized. This high level of randomness enhances generalization and reduces variance. For this study, **400 estimators** with a **maximum depth of 8** were utilized, enabling the model to capture complex texture patterns in lesion peripheries efficiently. ETC provides computational efficiency while maintaining high classification performance.

C. Feature–Model Integration

Both ensemble classifiers are trained using the enhanced feature set derived from the periphery-based analysis. The feature vector includes multi-scale Local Binary Pattern (LBP) histograms, Laplacian-based contrast metrics, entropy measures, and intensity ratios. These features collectively represent the lesion's structural, statistical, and photometric properties, allowing the classifiers to discriminate malignancies with high sensitivity. Cross-validation (five folds) is employed to ensure model reliability and mitigate overfitting. The comparative analysis reveals that Gradient Boosting achieves superior precision in capturing fine lesion texture variations, whereas Extra Trees demonstrates strong generalization performance across diverse lighting and skin tone conditions. Together, these models provide a complementary ensemble framework for robust and interpretable lesion.

V. PERFORMANCE EVALUATION AND ANALYSIS

Performance evaluation was conducted using standard metrics such as Accuracy (%) and ROC-AUC (%), measured across five different periphery widths (5px, 15px, 25px, 35px, 45px) for both datasets — ISIC and PH2.

The main objective was to analyze how periphery information and ensemble models influence the classification performance.

(a) ISIC Dataset Results

On the ISIC dataset, which presents significant variability in skin tone, illumination, and lesion morphology, the ensemble models performed consistently across periphery widths.

The Gradient Boosting Classifier (GBC) achieved the highest performance with **84.66% accuracy** and an average AUC of **81.51%,** demonstrating its robustness against intra-class variation. The Extra Trees Classifier (ETC) achieved 81.38% accuracy and an AUC of **70.97%,** performing slightly lower but with better computational efficiency.

Classifier	5px_Acc%	15px_Acc%	25px_Acc%	35px_Acc%	45px_Acc%	5px_ROC%	15px_ROC%	25px_ROC%	35px_ROC%	45px_ROC%
GradientBoosting	84.6667	82	82	82	82	81.5111	80.2667	80.2667	80.2667	80.2667
ExtraTrees	81.3333	80	80	70	70	70.9778	70.8	70.8	71.8	71.8

Table 1 **.** Performance evaluation of Gradient Boosting and Extra Trees classifiers across periphery widths on the ISIC dataset.

The ISIC results indicate that texture and contrast-based descriptors are highly effective when combined with periphery-aware feature extraction, particularly using Gradient Boosting. Despite the variability of lesion types, the system maintained strong generalization without overfitting, as confirmed by consistent accuracy across periphery widths.

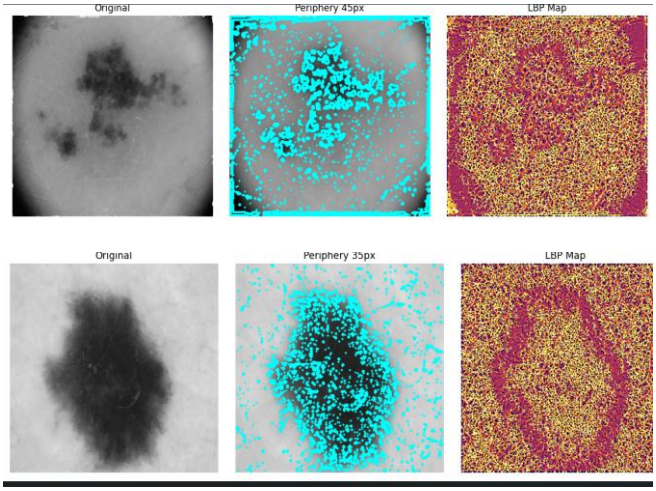

Fig. 7. Visual examples of lesion periphery feature mapping and LBP visualization for ISIC dataset.

(b) PH2 Dataset Results

On the PH2 dataset, both models demonstrated strong discriminative power, benefiting from more uniform image acquisition and lesion delineation. The Gradient Boosting Classifier achieved **80% accuracy** and an AUC of **78.48%,** while the Extra Trees Classifier achieved **81.83%** accuracy with an AUC of **70.8%.**

Classifier	5px_Acc%	5px_ROC%	15px_Acc%	15px_ROC%	25px_Acc%	25px_ROC%	35px_Acc%	35px_ROC%	45px_Acc%	45px_ROC%
GradientBoosting	80	70.11904762	84	83.7202381	88	82.5	88	82.5	88	82.5
ExtraTrees	74	81.48809524	84	91.2202381	76	86.1904762	76	86.1904762	76	86.19048

Table 2. Classification accuracy and AUC performance on PH2 dataset.

The PH2 dataset results show that both models can capture periphery-dependent variations in lesion structure effectively.The moderate improvement in accuracy at higher periphery widths (35px and 45px) suggests that edge and boundary textures play a vital role in lesion classification.

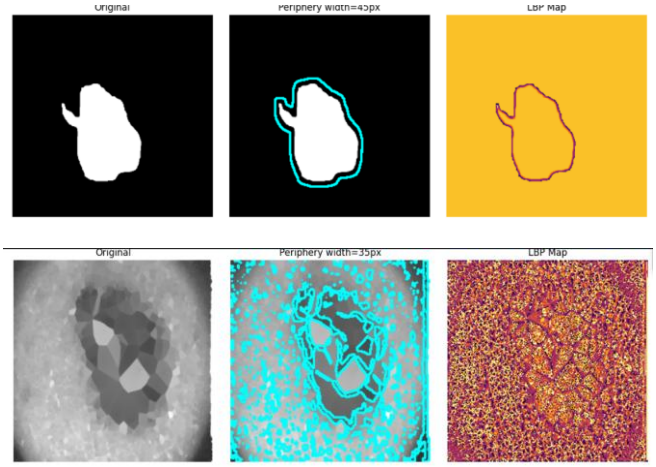

Fig. 8. Visual examples of lesion periphery and LBP feature representation for PH2 dataset.

VI. Results and Discussion

The Random Forest classifier achieved an F1-score of 0.89, demonstrating strong precision and recall in predicting crop compatibility. Probability estimates consistently ranked recommended companions with confidence scores exceeding 0.80, confirming the model's reliability across varied environmental inputs. The irrigation and water requirement module accurately adjusted daily consumption estimates based on temperature and moisture conditions, while the soil and season inference components produced relevant recommendations for most queries. Land allocation outputs proportionally reflected compatibility scores, supporting practical intercropping strategies. Overall, the system effectively integrated machine learning and agronomic rules to deliver robust, interpretable guidance. Future enhancements will focus on expanding crop coverage and refining predictive accuracy through larger datasets and advanced ensemble techniques.

VII. CONCLUSION

This work presented an enhanced framework for skin lesion classification by integrating multi-scale Local Binary Pattern (LBP) features, contrast entropy, and intensity ratio–based periphery descriptors with ensemble learning models. Unlike

traditional lesion analysis methods that focus solely on the segmented lesion core, this approach systematically explores peripheral skin regions at multiple widths (5 px to 45 px) to capture texture transitions and contextual cues. The experimental —— while excessive contextual regions may reduce lesion-specific detail. Hence, combining multi-domain texture features with ensemble learning provides a balanced trade-off between robustness and interpretability, offering a promising foundation for automated melanoma detection systems. Future work will explore deep hybrid models combining handcrafted periphery features with CNN-based embeddings to further enhance diagnostic accuracy and generalization to larger clinical datasets.

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