

A New Framework for Automated Skin Cancer Classification based on Multifractal Feature Extraction using Random Forest

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ABSTRACT:

Skin cancer is a major public health concern, and early accurate classification is essential for improving diagnosis and treatment outcomes. However, differentiating basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma remains challenging because of their visual similarity, irregular lesion borders, and heterogeneous morphological patterns. This study proposes an automated skin cancer classification framework based on multifractal feature extraction and Random Forest classification. A total of 1,043 dermoscopic images collected from ISIC and Kaggle repositories were used, including 454 melanoma, 392 BCC, and 197 SCC cases. The images were preprocessed through grayscale conversion, adaptive binarization, and region-of-interest preparation. Multifractal descriptors, including generalized dimensions and singularity spectrum features, were then extracted to quantify lesion complexity, spatial irregularity, and textural heterogeneity. These features were used to train a Random Forest classifier for three-class classification. The proposed framework achieved 98.8% accuracy, 98.8% sensitivity, 98.8% precision, 98.8% F-score, and 99.4% specificity. The results demonstrate that multifractal analysis combined with machine learning provides an accurate, interpretable, and computationally efficient approach for automated skin cancer classification..

Keywords: Basal Cell Carcinoma; Melanoma; Multifractal; Random Forest; Skin cancer; Squamous Cell Carcinoma

1. Introduction

The skin is the largest protective organ of the human body, acting as a barrier against trauma, envi-

ronmental stress, harmful chemicals, microorganisms, and ultraviolet radiation [1]. Skin cancer has become a major global health concern, with recent

cancer statistics reporting more than 20 million new cancer cases worldwide in 2022, including non-melanoma skin cancers [2,3]. Globally, more than 1.5 million new skin cancer cases and approximately 125,000 related deaths are reported annually, highlighting the urgent need for early and accurate diagnosis [4,5]. Among the major skin cancer types, basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma are clinically important because of their high incidence, diagnostic difficulty, and potential severity. Although non-melanoma skin cancer accounts for most recorded cases, melanoma remains the most aggressive form and is responsible for a large proportion of skin-cancer-related deaths [3].

Early classification of BCC, SCC, and melanoma remains challenging because these lesions often share similar visual characteristics, especially at early stages. Their irregular borders, heterogeneous pigmentation, complex texture, and overlapping morphological features can reduce diagnostic confidence and increase reliance on invasive biopsy procedures [6–8]. Therefore, automated computer-aided diagnostic systems have become increasingly important for supporting dermatologists, improving diagnostic consistency, and accelerating clinical decision-making.

Recent studies have explored several artificial intelligence and image-analysis approaches for skin cancer detection and classification. Deep learning models, including CNN-based architectures, Xception, VGG16, ResNet, Vision Transformers, and attention-based networks, have demonstrated promising performance on public datasets such as HAM10000, ISIC, PH2, and Kaggle-derived collections [10,12–16,19,24,27–35]. Other studies have combined preprocessing, segmentation, feature extraction, transfer learning, reinforcement learning, generative models, and explainable AI to improve classification accuracy and robustness [25,29,30,33,36,37]. Despite these advances, many deep learning approaches require large annotated datasets, extensive training procedures, high computational resources, and may suffer from limited interpretability [38].

In parallel, fractal-based methods have been investigated as mathematical tools for describing the irregular geometry and structural complexity of skin lesions. Previous studies used fractal dimension, differential box counting, Higuchi fractal descriptors, and box-counting analysis to quantify lesion shape, texture, and histological complexity [11,17,18,21,22,26]. However, conventional monofractal analysis usually provides a single global descriptor, which may be insufficient to capture the heterogeneous and locally varying patterns of cancerous lesions. Multifractal analysis offers a more comprehensive framework by characterizing lesion morphology across multiple scaling behaviors and local singularities [9].

Based on this motivation, the present study proposes an automated skin cancer classification framework using multifractal feature extraction and Random Forest classification. The proposed method extracts discriminative multifractal descriptors from dermoscopic images to represent lesion complexity, spatial irregularity, and textural heterogeneity. These features are then used to classify three major skin cancer types: BCC, SCC, and melanoma. The main contribution of this study is the development of an interpretable and computationally efficient classification framework that combines the descriptive power of multifractal geometry with the robustness of machine learning, providing a reliable alternative to highly complex deep learning-based systems.

2. Research Methodology

The proposed research methodology, illustrated in **Figure 1**, was developed as an automated and interpretable framework for three-class skin cancer classification using dermoscopic images. The overall workflow consists of six sequential stages: dataset acquisition, dataset preparation, image preprocessing, multifractal feature extraction, feature-based classification, and performance evaluation. The main objective of this workflow is to combine mathematical characterization of lesion morphology with machine learning-based classification in order to achieve accurate, interpretable, and computationally efficient skin cancer diagnosis.

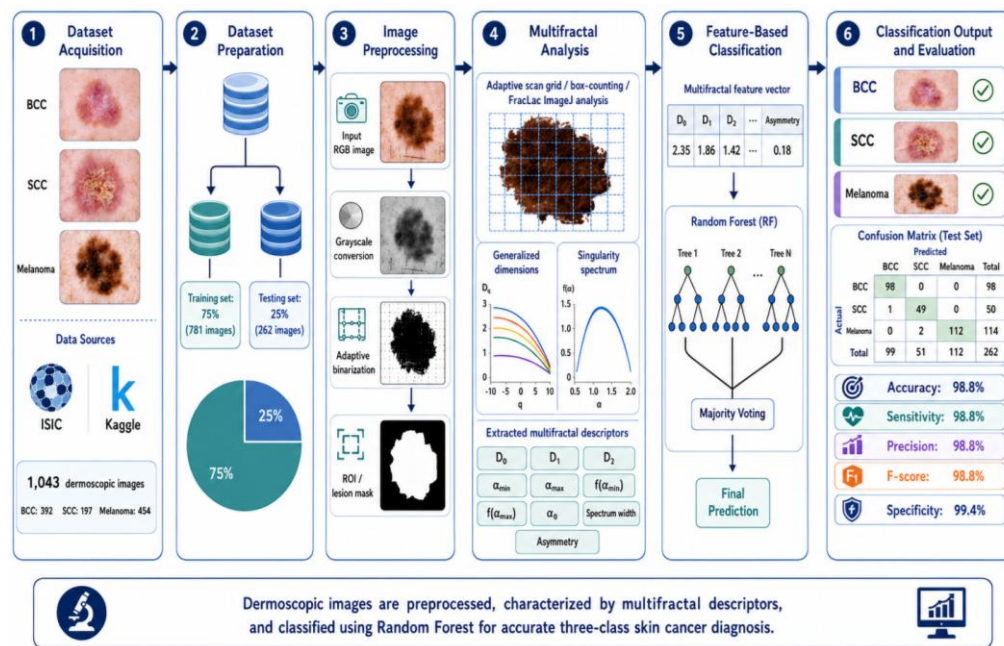


Figure 1. Research methodology of the proposed automated skin cancer classification framework

2.1. Dataset Acquisition and Preparation

In the first stage, dermoscopic images were collected from two publicly available repositories, namely ISIC and Kaggle [38]. The dataset comprised three clinically important skin cancer classes: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. These categories were selected because they represent common and diagnostically challenging skin cancer types with overlapping visual and morphological characteristics. In total, 1,043 dermoscopic images were used in this study, including 392 BCC images, 197 SCC images, and 454 melanoma images.

Table 1. Dataset distribution used for training and testing of the proposed skin cancer classification framework [39].

Type	Samples	Training samples (75%)	Testing samples (25%)
Melanoma	454	340	114
BCC	392	294	98
SCC	197	147	50
Total samples	1043	781	262

2.2. Image Preprocessing

In the second stage, an image preprocessing workflow was applied to prepare each dermoscopic im-

age for quantitative multifractal analysis. As shown in **Figure 1**, the preprocessing stage started with the original RGB dermoscopic image. Each image

age for quantitative multifractal analysis. As shown in **Figure 1**, the preprocessing stage started with the original RGB dermoscopic image. Each image

was then converted into grayscale format to reduce color complexity while preserving the structural information of the lesion. After that, adaptive binarization was applied to separate the lesion region from the surrounding skin background. Finally, a region-of-interest (ROI) mask was generated to isolate the lesion area and provide a binary structure suitable for box-counting and multifractal feature extraction.

2.3. Multifractal Feature Extraction

The third stage represents the mathematical core of the proposed framework. Multifractal analysis was applied to extract descriptors capable of characterizing the irregularity, heterogeneity, and spatial complexity of skin lesions. Unlike conventional monofractal analysis, which describes an object using a single global fractal dimension, multifractal analysis provides a spectrum of scaling properties

that reflects both global and local structural variations.

As illustrated in **Figure 2(a)**, the generalized dimensions (D_q) describe how lesion complexity changes with the statistical moment (q). The curve includes important descriptors such as (D_0), (D_1), and (D_2), which represent the capacity dimension, information dimension, and correlation dimension, respectively. These descriptors quantify different aspects of lesion geometry, pixel distribution, and spatial correlation. **Figure 2(b)** further illustrates the singularity spectrum ($f(\alpha)$), which describes the distribution of local singularities within the lesion. Parameters such as (α_{min}), (α_{max}), spectrum width, and asymmetry provide additional information about lesion heterogeneity and local morphological variation.

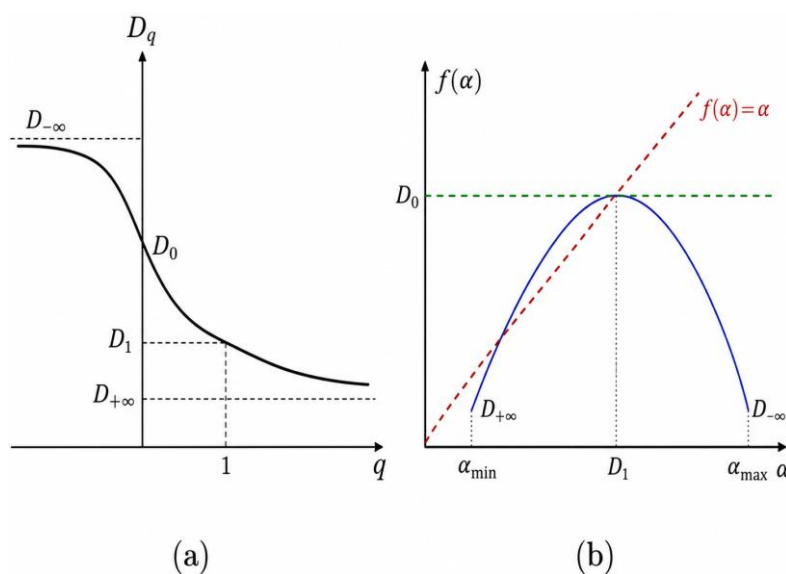


Figure 2. Mathematical representation of the multifractal framework used in the proposed methodology: (a) generalized dimensions D_q ; (b) singularity spectrum.

The multifractal analysis was performed using an adaptive scan grid and box-counting procedure through FracLac/ImageJ-based analysis. The extracted feature set included (D_0), (D_1), and (D_2), (α_{min}), (α_{max}), ($f(\alpha_{min})$), ($f(\alpha_{max})$), (α_0), spectrum width, and asymmetry. These descriptors were then organized into a numerical feature vector for classification.

2.4. Feature-Based Classification Using Random Forest

In the fourth stage, the extracted multifractal descriptors were used as input features for a Random Forest (RF) classifier, as shown in Figure 1. Random Forest was selected because it is robust, interpretable, resistant to overfitting, and suitable for feature-based medical image classification. The RF

classifier consists of multiple decision trees, where each tree produces an independent prediction based on a subset of features and training samples. The final class label is determined using majority voting across all trees. This ensemble decision strategy improves classification stability and reduces the effect of noisy or weak individual decision rules.

2.5. Model Evaluation

In the final stage, the trained RF model was evaluated using the independent testing subset. The classification output included the three target classes: BCC, SCC, and melanoma. Model performance was assessed using a confusion matrix and standard evaluation metrics, including accuracy, sensitivity, precision, F-score, and specificity. The proposed framework achieved an overall accuracy of 98.8%, sensitivity of 98.8%, precision of 98.8%, F-score of 98.8%, and specificity of 99.4%. These results demonstrate that combining multifractal descriptors with Random Forest classification provides an accurate, interpretable, and computationally efficient framework for automated skin cancer classification.

3. Research Results

3.1. The image preprocessing

The image preprocessing workflow is illustrated in **Figure 3** as an operation-based diagram showing

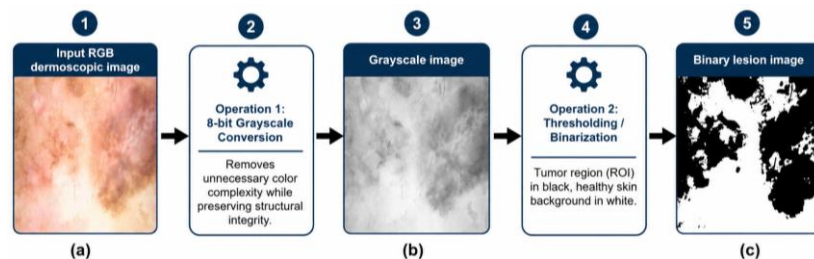


Figure 3. Image preprocessing operation diagram. The raw RGB dermoscopic image is first converted into an 8-bit grayscale image to reduce color complexity while preserving lesion structure. The grayscale image is then transformed into a binary lesion image using thresholding/binarization, where the tumor region of interest is represented in black and the surrounding healthy skin background is represented in white.

3.2. Multifractal analysis and features extraction

Multifractal analysis was performed using ImageJ software version 1.54g together with the FracLac

the transformation from the raw dermoscopic image to the final binary lesion image. First, the input RGB dermoscopic image, shown in **Figure 3(a)** was converted into an 8-bit grayscale image through grayscale conversion [40]. This operation reduces unnecessary color complexity while preserving the essential structural information of the lesion, including intensity variation, tissue density, and spatial distribution patterns. Since multifractal analysis operates efficiently on single-channel intensity images, grayscale conversion provides a suitable representation for subsequent quantitative analysis [41]. After grayscale conversion, the resulting image, shown in **Figure 3(b)**, was processed using a thresholding-based binarization operation. In this step, the grayscale image was converted into a binary image in order to distinguish the tumor region from the surrounding healthy skin background. The lesion region of interest (ROI) was represented in black, while the background was represented in white, as shown in **Figure 6(c)**. This binary representation is essential for box-counting and multifractal analysis because it provides a clear structural map of the lesion area [42]. Therefore, the preprocessing stage prepares the dermoscopic images for reliable extraction of multifractal descriptors by simplifying the image representation while preserving the morphological characteristics required for classification.

plugin, which is specifically designed for analyzing complex, irregular, and heterogeneous biological structures. After completing the preprocessing stage, each dermoscopic image was processed

through three sequential representations: the original source image, the grayscale image, and the binary lesion image [43]. The binary image was then used as the main input for multifractal analysis, where the lesion structure was examined using a box-counting-based procedure to extract the corresponding $(f(\alpha))$ singularity spectrum.

Figure 4 presents representative examples of the multifractal analysis workflow for the three investigated skin cancer classes: BCC, SCC, and melanoma. For each class, the figure shows the source dermoscopic image, the corresponding grayscale image, the generated binary image, and the resulting $(f(\alpha))$ spectrum. These examples demonstrate how visual lesion information is transformed into quantitative multifractal descriptors. The source images show the original color and texture characteristics of the lesions, while the grayscale images preserve the intensity distribution required for sin-

gle-channel analysis [44]. The binary images emphasize the spatial distribution of the lesion region and provide a simplified structural representation suitable for box-counting analysis.

The $(f(\alpha))$ spectra shown in **Figure 4** reflect the multifractal behavior of the lesion patterns. Differences in the shape, width, and peak position of the spectra indicate variations in lesion heterogeneity, local irregularity, and spatial complexity among the three cancer classes. Therefore, the singularity spectrum provides important quantitative information that cannot be fully captured by visual inspection alone [45]. Based on this analysis, several multifractal descriptors were extracted, including generalized dimensions and singularity spectrum parameters. These features were subsequently used as discriminative inputs for the Random Forest classifier.

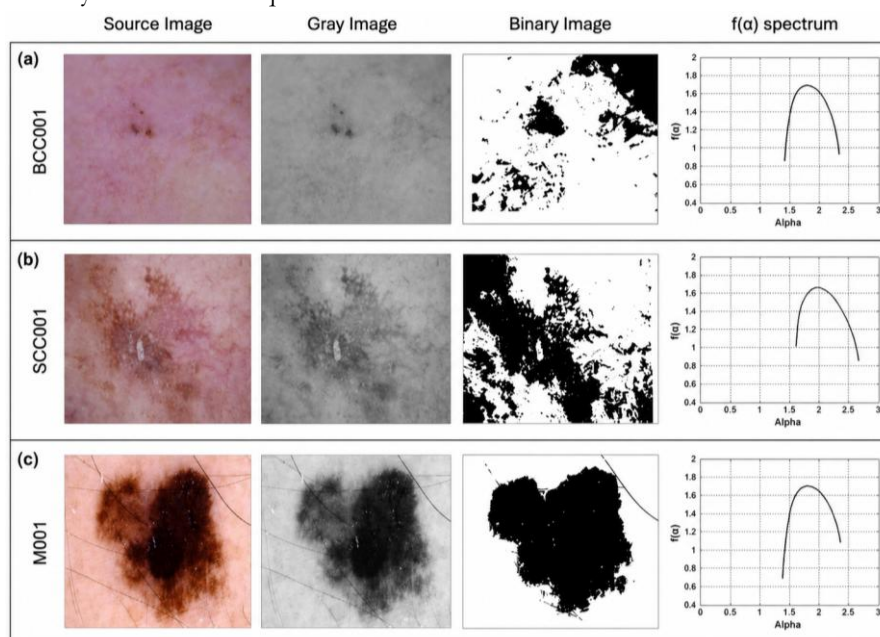


Figure 4. Representative multifractal analysis workflow for the three skin cancer classes. The figure shows one representative sample from each class: (a) BCC001, (b) SCC001, and (c) M001. For each sample, the source dermoscopic image was converted into a grayscale image and then transformed into a binary lesion image. The binary representation was used for box-counting-based multifractal analysis to generate the corresponding $(f(\alpha))$ singularity spectrum, which reflects lesion heterogeneity, spatial irregularity, and local morphological complexity.

3.3. Performance Measures

The classification performance of the proposed Random Forest model is presented in **Figure 5**.

Figure 5(a) shows the class-wise classification results for the three investigated skin lesion categories: BCC, SCC, and melanoma. The testing subset included 262 images, consisting of 98 BCC images,

50 SCC images, and 114 melanoma images. The model correctly classified all BCC images, achieving 98 correctly classified cases out of 98, with no misclassified samples. For SCC, the model correctly classified 49 images out of 50, with only one misclassified case. For melanoma, 112 images were correctly classified out of 114, while only two images were misclassified. Accordingly, the model correctly classified 259 images out of 262 testing samples, resulting in an overall classification accuracy of 98.8%.

These results indicate that the proposed feature-based classification approach has strong discriminative capability across the three lesion classes. The absence of misclassified BCC samples demonstrates the model's ability to identify the multifractal patterns associated with BCC lesions. Although SCC and melanoma showed a small number of misclassified cases, the error rate remained very low, indicating that the extracted multifractal descriptors were effective in capturing the morphological and textural differences among the three classes.

Figure 5(b) summarizes the main performance metrics of the Random Forest classifier. The model achieved a sensitivity of 98.8%, specificity of 99.4%, precision of 98.8%, and F-score of 98.8%. The high sensitivity indicates that the model was highly effective in identifying positive lesion cases, while the high specificity confirms its ability to correctly distinguish non-target cases and reduce false classifications. Similarly, the high precision demonstrates the reliability of the predicted class labels, and the F-score confirms the balanced performance between sensitivity and precision.

Overall, the results shown in **Figure 5** confirm that combining multifractal feature extraction with Random Forest classification provides a robust and accurate framework for automated skin cancer classification. The high classification accuracy and balanced evaluation metrics indicate that the proposed method can effectively support the differentiation of BCC, SCC, and melanoma using interpretable mathematical descriptors extracted from dermoscopic images.

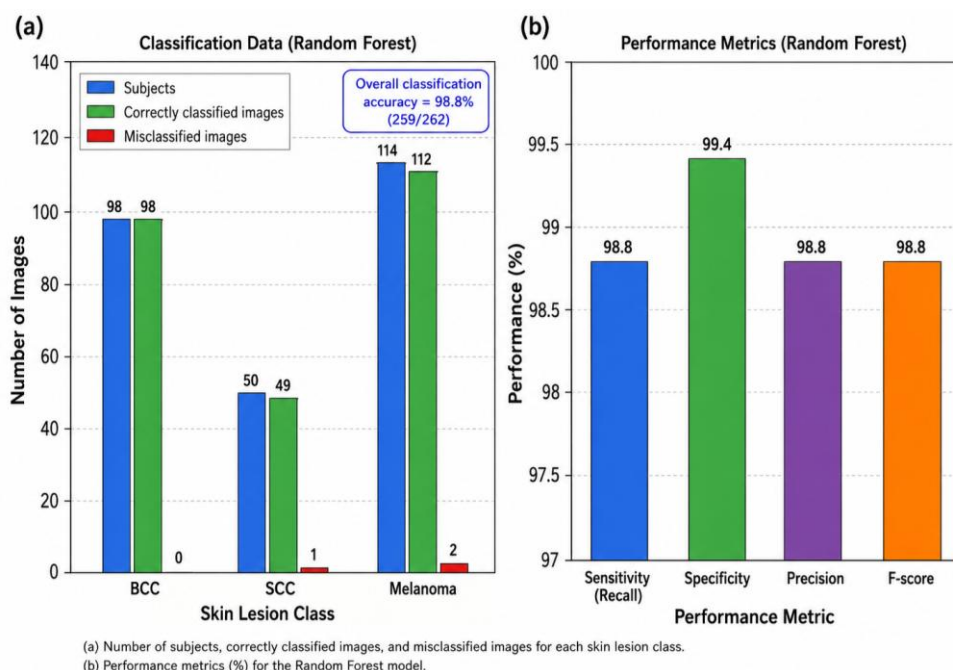


Figure 5. Random Forest classification results and performance metrics. (a) Class-wise classification results showing the number of testing subjects, correctly classified images, and misclassified images for BCC, SCC, and melanoma. The model correctly classified 259 out of 262 testing images, achieving an overall classification accuracy of 98.8%. (b) Performance metrics of the Random Forest classifier, including sensitivity, specificity, precision, and F-score.

4. Conclusion

This study proposed an automated and interpretable framework for skin cancer classification based on multifractal feature extraction and Random Forest classification. The proposed framework was designed to classify three clinically important skin cancer types: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. These classes are diagnostically challenging because of their visual similarity, irregular borders, heterogeneous texture, and overlapping morphological characteristics.

The methodology was based on transforming dermoscopic images into quantitative mathematical representations. First, RGB dermoscopic images were converted into grayscale images to reduce color complexity while preserving the structural characteristics of the lesion. Then, thresholding-based binarization was applied to generate binary lesion images suitable for box-counting analysis. After preprocessing, multifractal analysis was performed using ImageJ and the FracLac plugin to extract discriminative descriptors from the lesion structure. These descriptors included generalized dimensions and singularity spectrum parameters, such as (D_0) , (D_1) , and (D_2) , (α_{min}) , (α_{max}) , $(f(\alpha_{min}))$, $(f(\alpha_{max}))$, spectrum width, and asymmetry.

The extracted multifractal features were then used as input to a Random Forest classifier. The model was evaluated using an independent testing set containing 262 dermoscopic images. The proposed classifier correctly classified 259 images out of 262, achieving an overall classification accuracy of 98.8%. The model also achieved sensitivity of 98.8%, precision of 98.8%, F-score of 98.8%, and specificity of 99.4%. These results indicate that the extracted multifractal descriptors were highly effective in representing the morphological complexity and spatial heterogeneity of skin lesions.

The classification results demonstrated strong performance across all investigated classes. All BCC cases were correctly classified, while only one SCC case and two melanoma cases were misclassified. This confirms that the proposed feature-based framework can effectively distinguish between the three skin cancer types using mathematically interpretable descriptors rather than relying on complex deep learning architectures. Therefore, the proposed approach provides an accurate, computationally efficient, and explainable alternative for automated skin cancer classification.

A comparative analysis with previous related studies further supports the effectiveness of the proposed framework. As shown in **Figure 6**, previous fractal-based and machine-learning approaches reported classification accuracies ranging from 88.0% to 95.42% across different datasets, including PH2, ISIC, Med-Node, 7-Point, and clinical dermoscopic image datasets. In comparison, the proposed multifractal-Random Forest framework achieved the highest reported accuracy of 98.8% using images collected from Kaggle and ISIC libraries. Although direct comparison is influenced by differences in datasets, class definitions, and experimental settings, the proposed method shows a clear performance advantage over the compared studies. This improvement highlights the benefit of using multifractal analysis, which captures both global and local lesion irregularities more effectively than conventional monofractal descriptors.

Overall, the findings confirm that combining multifractal geometry with Random Forest classification can provide a reliable decision-support framework for automated skin cancer diagnosis. Future work should focus on validating the proposed method using larger multicenter datasets, external clinical cohorts, and cross-dataset testing. In addition, integrating clinical metadata and evaluating the system under real-world diagnostic conditions could further improve its robustness and clinical applicability.

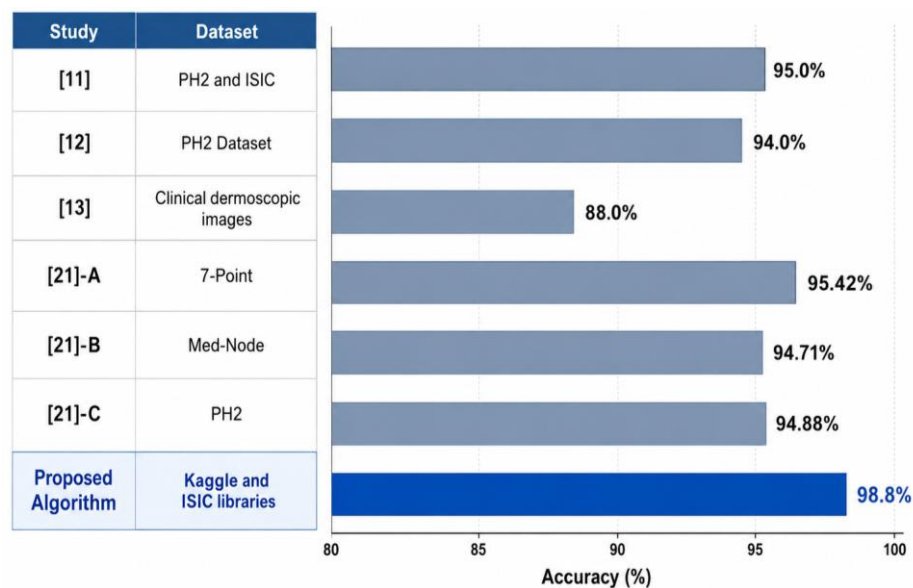


Figure 6. Comparative analysis of classification accuracy across related studies and the proposed method. The figure compares the reported accuracy values of previous fractal-based and machine-learning studies using different datasets, including PH2, ISIC, Med-Node, 7-Point, and clinical dermoscopic images. The proposed multifractal-Random Forest framework achieved the highest accuracy of 98.8% using Kaggle and ISIC libraries.

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