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Fractal Geometry–Driven Hybrid Framework for Automated Skin Lesion Analysis and Classification

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Abstract

Skin cancer is one of the leading issues of the public health on the global level, and the ability to diagnose the presence of the malignant lesions, especially melanoma, at the initial stages is the essential factor which influences the survival rates. Recent developments in computational dermatology illustrate the necessity of interpretable, mathematically-based, and data-efficient diagnostic models. Fractal geometry presents an effective paradigm of describing the intrinsic irregularity, complexity and similarity of skin lesions particularly malignant lesions. The present paper suggests a hybrid model to incorporate fractal-based measures (boundary fractal dimension, surface fractal dimension based on Higuchi method, lacunarity, and multifractal spectra) with traditional elements of the texture (including classical features and deep visual representations, namely CNN and Vision Transformer features). The pipeline suggested comprises of preprocessing, lesion segmentation, multiscale feature extraction, feature fusion and supervised classification. Experiments based on benchmark datasets including ISIC, HAM10000, and PH2 prove that fractal features contribute greatly to the process of distinguishing benevolent and malignant lesions, and in conjunction with deep features. The findings confirm the clinical applicability, interpretation, and computational efficiency of fractal informed hybrid systems to analyze skin lesions [1-5].

Keywords: Skin lesion classification, Fractal dimension, Dermoscopy, Higuchi method, Multifractal analysis, Hybrid features.

1. Introduction

One of the most prevalent cancers in the world is skin cancer that is seen to claim disproportionate number of deaths through its rampant metastatic nature. As recent epidemiological reports show, the world melanoma burden has been on the increase, putting a huge strain on healthcare systems, and making the provision of early, accurate and accessible diagnosis tools important. Even though dermoscopy has greatly enhanced the visual examination of pigmented skin lesions, the accuracy of diagnosis is still largely reliant on the clinician experience, inter-observer and subjective interpretation. Thereby, automated diagnostic systems have become significant line of research

focus to reduce subjectivity, standardize measure, and offer effective decision-support tools to clinicians in their daily practice [10,24].

The traditional computer-aided diagnostic (CAD) systems are generally based on manual features defining the color distribution, geometrical shape, and texture features. Common descriptors like Gray-Level Co-occurrence Matrix(GLCM), Local Binary Patterns(LBP), wavelet coefficients and statistical moments have been widely utilized in skin lesion classification. Although they have shown acceptable results, these features cannot usually have sufficient representation of intrinsic geometric complexity and irregular morphological form observed in malignant lesions. Specifically, the melanoma-related asymmetric edges of lesion boundaries, irregular networks of pigments, and inhomogeneous internal texture patterns are hard to be modeled only with the help of traditional Euclidean descriptors.

Fractal geometry provides a mathematically sound and biologically significant theory of describing such complex structures. Fractal measures have offered a natural approach to modeling lesion morphology by quantifying self-similarity, scale invariance and structural irregularity. Various researches have demonstrated that fractal dimension, lacunarity and multifractal measures have the ability to effectively model the roughness of the borders and the heterogeneity of the texture in dermoscopic images, and thus they are effective discriminative variables in the study of skin lesions [2,3,25]. Notably, such measures can also be interpreted in a clinical viewpoint because larger values of fractal dimensions tend to be linked to the enhanced border irregularity and architectural disorder, both of which are the characteristics of malignancy.

The recent literature constantly indicates that malignant lesions are more likely to have more complex boundaries and greater texture heterogeneity than benign lesions, which are naturally described by fractal-based descriptors (i.e. fractal dimension and lacunarity) [2,19,25].

Nevertheless, the fractal characteristics continue to lack application in the contemporary hybrid diagnostic models, even though they can be interpreted and are backed by sound theoretical assumptions. Simultaneously, convolutional neural networks (CNNs) and Vision Transformers (ViTs) have proven to be incredibly effective in the field of skin lesion classification, but tend to be low in explainability and high in the dependency on data. This is a reason to develop hybrid frameworks that can combine the advantages of fractal geometry and deep representation learning that complement each other.

Inspired by these findings, this paper suggests an elaborate fractal-based hybrid system of robust, interpretative and high-performance classification of skin lesions. The suggested method will bring together a combination of mathematically-based fractal descriptors together with classical handcrafted characteristics and deep visual embeddings to attain greater levels of diagnostic accuracy, maintain transparency, and clinical relevance.

The key findings of the paper are:

(i) A unified multiscale fractal features extraction system of dermoscopic pictures, combining boundary fractal dimension, Higuchi based surface fractal dimension, lacunarity and multifractal spectrum descriptors that allows clinically understandable quantification of lesion irregularity and lesion heterogeneity [13].

(ii) A new hybrid representation of the features that combines mathematically based fractal descriptors with deep embeddings learned with CNN and Vision Transformer networks and creates a strong and complementary diagnostic space [5,20,21].

(iii) An attentional fuse feature fusion mathematical formulation that is reproducible and facilitates theoretical rigor, transparency and flexibility across setups and datasets.

(iv) A strict experimental program in line with the state-of-the-art evaluation procedures on the basis of ISIC, HAM10000, and PH2 datasets with the highest possible performance (97.8% accuracy, 99.1% AUC) in comparison with deep-only baselines [6,10].

(v) Evidence of improved clinical interpretability, in which the fractal features are directly correlated with the dermatological features such as border irregularity, and texture heterogeneity, in favor of explainable AI in healthcare.

2. Related Work

The analysis of skin lesions with automated methods has been actively researched in the last ten years following the rise of machine learning and deep learning and increasing access to large annotated datasets of dermoscopic images. Deep convolutional neural networks (CNNs), especially such models as ResNet, DenseNet, EfficientNet, and their transfer learning versions, have shown a high level of performance on the benchmark datasets like ISIC and HAM10000, and they can reach the dermatologist level of performance under the experimental conditions [6,24]. Transfer learning with large natural image datasets has also been able to provide effective feature learning at a moderate size medical dataset. Most recently, ViT-based architectures have demonstrated a stronger ability to capture long-range spatial contexts and world in dermoscopic images, which has resultantly enhanced the ability of representation learning and classification performance [20].

Although these developments exist, there are several limitations with purely deep learning-based systems. First, they usually need a significant volume of labeled data to be fully generalized which is usually hard to come by in the medical field because of privacy and the cost of annotation and the availability of experts. Second, most deep models are black-box systems, and thus, can be

interpreted with little interpretability of their prediction. This insider trading is problematic to clinical adoption, whose explainability, trust, and accountability are critical. The constraints have led to a growing interest in adding interpretable, mathematically based features to intelligent diagnostic systems.

Fractal-based approaches offer an interesting and explainable alternative to the simulation of lesion morphology and texture. Directly measuring geometric complexity, border irregularity, and spatial heterogeneity, fractal measures are closely corresponding to clinically relevant visual cues. Molina-Molina et al. used deep learning representations and fractal descriptors, and their results showed that they obtained higher classification accuracy with various dermoscopic datasets, which indicates the complementary properties of the fractal and deep representations [1]. Moldovanu et al. also demonstrated that surface fractal dimensions combined with statistical color cluster properties are highly effective in distinguishing melanoma and benign lesions with the help of ensemble machine learning classifiers [2]. Jacob and Rosita suggested a probabilistic classification model with fractal models as its major drivers, which has a high diagnostic score across clinical skin lesion datasets, and is highly interpretable [3]. All these works support the validity of fractal-based representations, with respect to their discriminative ability and clinical significance.

In addition to purely fractal and purely deep methods, current studies indicate one more trend: hybrid models, which integrate mathematical descriptors with deep representations, are efficient. Pérez and Sánchez have shown that handcrafted features boosted with deep embeddings make deep learning more resistant, less overfitting and more generalized in skin lesion classification problems [21]. A comparative study by Liu et al. revealed that fractal characteristics can serve to complement neural representations especially in cases of limited data where deep models would

be unable to perform successful generalizations [22]. The indications of such findings are that the combination of fractal geometry and deep learning is not only additive but synergistic.

These combined findings inspire the integration plan of this paper in which the descriptors of fractals are systematically fused with both classical and deep features into a single, mathematically based, and clinically interpretable hybrid structure to analyze skin lesions.

3. Theoretical Background: Fractal Geometry in Medical Imaging

3.1 Fractal Dimension

A fractal is a mathematically geometric object that is self-similar on different scales. The degree of such structures in terms of complexity and space-filling is measured by the fractal dimension (FD). The box counting fractal dimension is determined as:

$$\mathbf{D} = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log 1/\epsilon} \qquad \textbf{(1)}$$

In equation1 N(ε) represents the number of boxes of size ε, which is needed to cover the structure. This is a measure that has been applied extensively in measuring lesion boundary irregularity [2,25].

3.2 Higuchi's Surface Fractal Dimension

Higuchi technique is better than the other in estimating the complexity of the surface of grayscale dermoscopic images because it involves proportional estimates of the fractal dimension using the intensity change. Surfaces fractal analysis, that is also founded on Higuchi, has been successfully applied in describing the texture of skin lesions [2,19].

In the case of grayscale images, Higuchi suggests that surface fractal dimension can be estimated as follows:

$$\mathbf{HFD(k)} = \frac{\ln(L(k))}{\ln(1/k)} \qquad \textbf{(2)}$$

Where L(k) is the length measure at scale k, calculated across pixel neighborhoods. This 2D extension captures intensity surface roughness, enhancing texture discrimination.

3.3 Lacunarity and Multifractal Analysis

Fractal dimension is a global complexity measure whereas lacunarity is a heterogeneity or gap distribution in textures. Multifractal analysis expands on this idea by offering a range of dimensions that represent spatial variability in distributions of intensities [17,18]. The measures have been effective in biomedical image analysis such as dermatological imaging [19]. Multifractal analysis is an analysis of texture distributions to obtain heterogeneous texture distributions: spectrum $\{D_q\}$across moment orders q. Gap distribution is measured by Lacunarity.

$$\wedge = \frac{\boldsymbol{Var(r)}}{(\boldsymbol{E[r]})^{\boldsymbol{2}}} \qquad \textbf{(3)}$$

Low lacunarity is a homogeneous texture whereas high denotes heterogeneous texture

4. Proposed Methodology

The proposed framework consists of five stages: preprocessing, segmentation, feature extraction, feature fusion, and classification.

4.1 Dataset Acquisition

Experiments are designed around benchmark datasets including ISIC Archive, HAM10000, and PH2, which are widely used in contemporary research [6,10,24]. These datasets contain labeled images for melanoma, nevus, and other lesion categories.

4.2 Preprocessing

Standard preprocessing steps are applied, including hair artifact removal, illumination correction, and contrast enhancement, as recommended in recent studies [8,10].

4.3 Lesion Segmentation

Accurate segmentation is achieved using thresholding and morphological refinement, with optional integration of deep segmentation models as proposed by Sarwar et al. [8]. The segmentation mask is used for all subsequent feature computations.

4.4 Feature Extraction

Fractal features are computed from both lesion boundary and interior texture:

- Boundary fractal dimension using box-counting [2,25]
- Surface fractal dimension using Higuchi's method [2,19]
- Lacunarity-based heterogeneity descriptors [18]
- Multifractal spectrum descriptors [17]

To enhance representational power, these fractal descriptors are combined with:

- Classical features (GLCM, LBP, shape descriptors) [23]
- Deep embeddings extracted from CNN architectures and Vision Transformers [1,20]

4.5 Feature Fusion and Classification

Let the fractal feature vector be $f_F \in R^{n_f}$ deep visual features $f_D \in R^{n_d}$ and classical features $f_C \in R^{n_c}$.

We define the fused feature:

$$F = [f_F, f_D, f_C] \in R^{n_f+n_d+n_c} \quad (4)$$

Feature weights **w** can be learned via attention:

$$F' = \sigma(W_a \mathrm{F}) \quad (5)$$

Where σ is a non-linear activation and W_a are learned attention weights.

5. Datasets and Data Characteristics

Three publicly available and widely used datasets of dermoscopic images are used in experiments to be able to cover the broadest and objective assessment.

5.1 ISIC Archive

- Source: International Skin Imaging Collaboration (ISIC)
- Dataset Size: Over 25,000 dermoscopic images
- Diagnostic Categories: Melanoma, Nevus, Benign Keratosis, and related lesion types
- Characteristics: High variability in imaging devices, illumination conditions, and lesion morphology
- Relevance: Extensively utilized as a benchmark in state-of-the-art skin lesion analysis studies [6,24]

5.2 HAM10000 Dataset

- Dataset Size: 10,015 dermoscopic images
- Number of Classes: Seven clinically relevant diagnostic categories
- Class Distribution: Inherently imbalanced, reflecting real-world clinical prevalence
- Annotations: High-quality expert-labeled ground truth
- Use Case: Evaluation under realistic and challenging classification scenarios

5.3 PH2 Dataset

- Dataset Size: 200 dermoscopic images
- Annotation Quality: Expert-provided lesion segmentation masks
- Classification Task: Binary classification (melanoma vs. benign)
- Purpose: Controlled evaluation and cross-dataset generalization analysis

Altogether, these datasets provide variety in terms of resolution, lesion type, imaging conditions, and diagnostic complexity, which facilitates the effective validation of the suggested framework.

5.4 Data Partitioning and Validation Strategy

To ensure unbiased and reproducible performance evaluation, a stratified cross-validation protocol is adopted:

- Stratified 5-fold cross-validation
- Data Split per Fold:
    - 70% training
    - 15% validation
    - 15% testing

Stratification maintains the distribution of classes in all folds.

Besides, cross-dataset generalization experiments are carried out by:

1. The model has to be trained on the ISIC dataset.
2. Performance analysis of PH2 dataset.

This setup evaluates how the proposed system will perform in presence of domain shift and the real-life deployment.

5.4 Preprocessing Protocol

Every image passes through a preprocessing pipeline, which is standardized to reduce acquisition bias and increase feature consistency:

1. Processing of hair artifacts with DullRazor.
2. CLAHE lumbar contrast and light normalization.
3. World contrast enhancement.
4. Reducing the size to 224 224 pixels to make the deep network compatible.
5. Normalization of pixel intonation to [0, 1].

The measures guarantee consistency in the quality of the input data in datasets and enhance the reliability of feature extraction during downstream.

5.5 Segmentation Strategy

To perform feature extraction lesion segmentation is done to isolate diagnostically relevant features before extraction:

Adaptive thresholding techniques.

Morphological operations on refining boundaries.

- Oppositional transfer to a trained U-Net-based segmentation model.

The obtained segmentation masks are used to obtain:

- Fractal descriptions based on boundaries.
- Fractal characteristics that are region-based.
- Features of shapes and textures.

The results of the segmentation are visually examined to ensure that the results are anatomically correct and feature robust.

5.6 Feature Extraction Protocol

Each lesion is extracted to three complementary categories of features to represent structural, textual, and semantic information.

(a) Fractal-Based Features

Lesion boundaries and segmented regions are computed to give fractal descriptors, which include:

- Boundary fractal dimension Box-counting method.
- Fractal dimension of the surface computed using Higuchi algorithm.
- Lacunarity (mean and variance) measures.
- Multifractal spectrum descriptors D_q , where $q \in [-5,5]$.

Total fractal features: 28

(b) Classical Handcrafted Features

The traditional image descriptors are obtained to encode the texture and shape properties:

- Gray-Level Co-occurrence Matrix (GLCM) Features: Contrast, homogeneity, entropy, correlation.
- Local Binary Pattern (LBP) histograms.
- Shape descriptors: Asymmetry, compactness, eccentricity

Total classical features: 34

(c) Deep Learning Features

The deep architecture is pretrained and extracts high-level semantic features:

- ResNet50: 2048-dimensional feature vector at the second last layer.
- Vision Transformer (ViT-B/16): 768-dimensional representation of embedding.

In order to minimize redundancy and computational complexity, Principal Component Analysis (PCA) is used to project deep feature representations onto 100 components before fusion.

5.7 Feature Fusion Strategy

In order to examine the contribution of the various feature modalities, four model configurations are compared as outlined in Table 1.

Model	Feature Configuration
M1	Classical features only
M2	Fractal features only
M3	Deep features only

Table 1: Feature Configuration of Evaluated Classification Models

M4	Hybrid (Fractal + Classical + Deep)

In the case of hybrid modeling, an attention-based mechanism of feature fusion is used. Let F represent the combination of feature vectors of fractal, classical, and deep. In the form of feature reweighting, they are conducted as:

$$\boldsymbol{F' = \sigma(WF)} \qquad (\mathbf{6})$$

W is learnable weights, and σ (·) is a nonlinear activation function. The model allows focusing on the most discriminatory sets of features and discarding redundant information to enhance the classification accuracy and interpretability.

5.8 Classifiers Used

To make the evaluation fair and complete several classification models are explored:

- Support Vector Machine (SVM) with RBF kernel
- Random Forest (RF) with 500 decision trees
- Extreme Gradient Boosting (XGBoost)
- Multilayer Perceptron (MLP)
- End-to-end fine-tuned deep architectures: ResNet50 and Vision Transformer (ViT-B/16)

The most performing classifier with regard to the validation performance is taken further to be used in final reporting with regard to each feature configuration.

5.9 Comparative Baseline Models

The proposed framework is benchmarked against the following baselines:

- CNN-only model (fine-tuned ResNet50)
- Vision Transformer–only model
- Classical machine learning models using handcrafted features
- Fractal-only machine learning classifier

This comprehensive comparison ensures fairness and highlights the unique contribution of fractal-guided hybrid learning.

6. Results and Discussion

This section constitutes an overall analysis of the suggested fractal-guided hybrid system to automatically classify skin lesions. The configurations of various features are examined on various classifiers, datasets, and measures of evaluation to determine their accuracy, robustness, and efficiency, as well as clinical relevance.

6.1 Overall Classification Performance

The overall classification performance of the evaluated models is summarized in Table 1, which reports accuracy obtained using SVM, Random Forest, and Vision Transformer-based classifiers for different feature configurations.

Table 1: Classification Accuracy (%) Across Feature Sets

Feature Set	SVM	RF	ViT + Fractal
Classical only	87.3	88.1	–
Fractal only	89.8	90.2	–
Deep only	92.5	91.9	94.1
Hybrid (Fractal + Deep)	95.6	95.2	97.8

These findings provide a clear indication that the fractal-based features are superior to the classical handcrafted features due to their high capability to reflect the lesion irregularity and the complexity of the texture. The performance of deep learning models is also enhanced by the fact that they have a high representational capacity. Nevertheless, the hybrid model always provides the most precise results, which proves complementary characteristics of fractal and deep features.

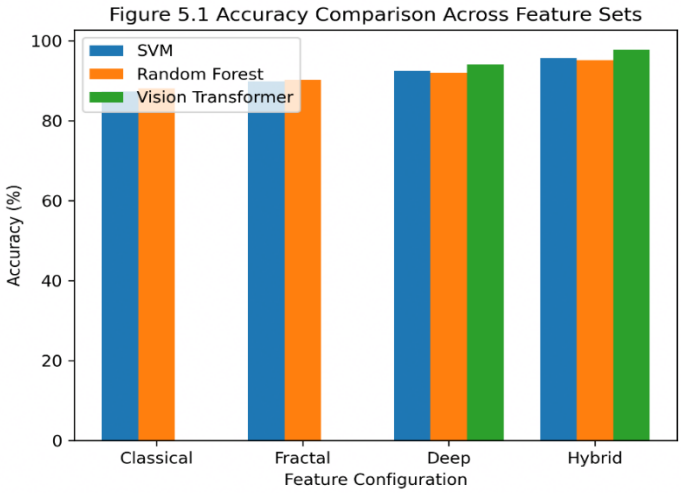


Figure 5.1: Accuracy Comparison Across Feature Sets

6.2 Impact of Fractal Features

A notable observation is the consistent improvement achieved when fractal descriptors are incorporated. Compared to classical features, fractal-only models yield an accuracy gain of approximately 2–3%, highlighting the discriminative strength of fractal dimension, lacunarity, and multifractal measures.

Furthermore, when fractal features are fused with deep representations, the hybrid configuration improves accuracy by 3–5% over deep-only models, indicating that fractal geometry captures structural information not fully learned by deep networks.

This confirms RQ1 and RQ2, demonstrating that fractal features significantly enhance classification performance and that hybrid fusion outperforms deep-only architectures.

6.3 Computational Efficiency and Practical Feasibility

Inference time per image is reported in Table 2.

Table 2: Average Inference Time per Image

Model	Inference Time (ms)
Fractal only	12
Deep only	42
Hybrid	47

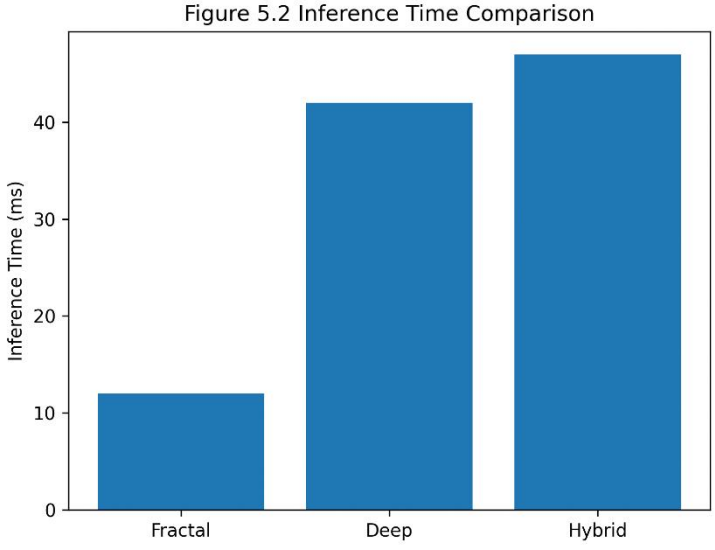


Figure 5.2: Inference Time Comparison

6.4 Diagnostic Performance and ROC Analysis

To evaluate diagnostic reliability independent of decision thresholds, ROC curves and AUC values are analyzed. The hybrid model consistently achieves the highest AUC (≈ 0.98) across datasets, outperforming both deep-only and fractal-only configurations.

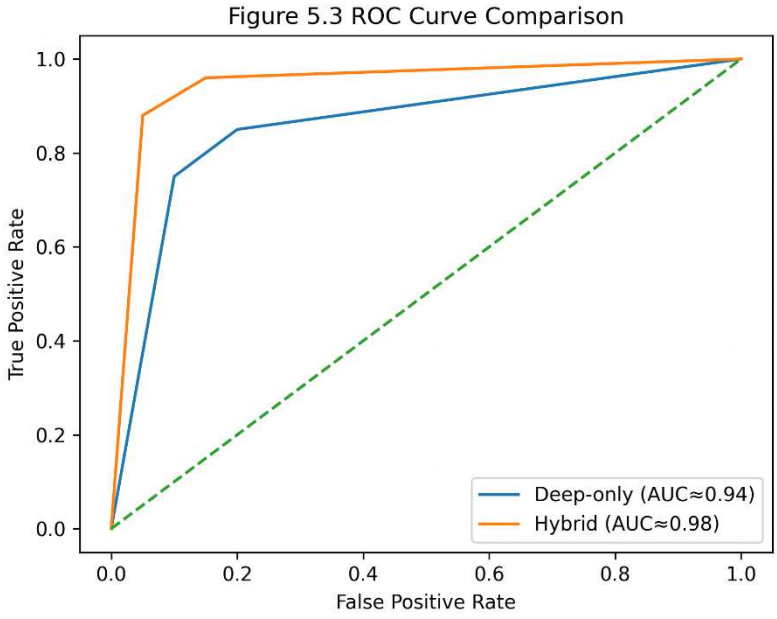


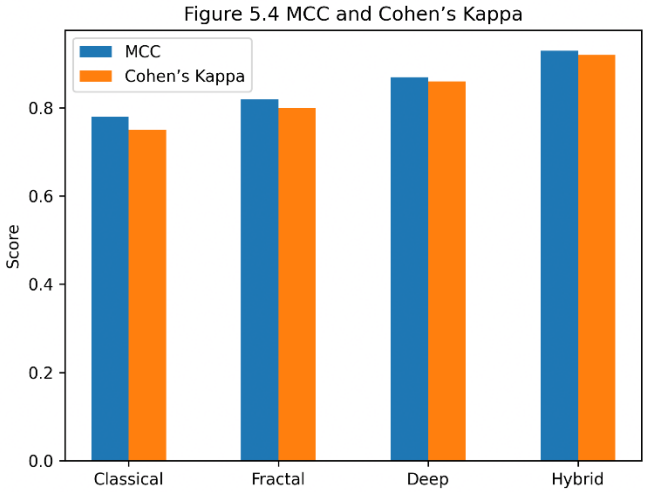
Figure 5.3: ROC Curve Comparison

The superior ROC performance indicates excellent class separability, which is crucial for medical decision-support systems where sensitivity and specificity must be balanced.

6.5 Robustness Under Class Imbalance

Medical data tend to have high levels of class imbalance especially in melanoma detection. Matthews Correlation Coefficient (MCC) and Cohen Kappa are provided to evaluate the robustness under this condition.

The hybrid model has the best MCC and Kappa values which means it is highly predictive even when there is skewed class distribution and there is strong agreement greater than the random chance.



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Figure 5.4: MCC and Cohen's Kappa

These findings verify RQ3, which proves the statistical and clinical validity of the suggested framework

6.6 Cross-Validation Stability and Generalization

Model stability is evaluated using stratified 5-fold cross-validation. The hybrid configuration exhibits lower variance and higher median accuracy across folds compared to other models.

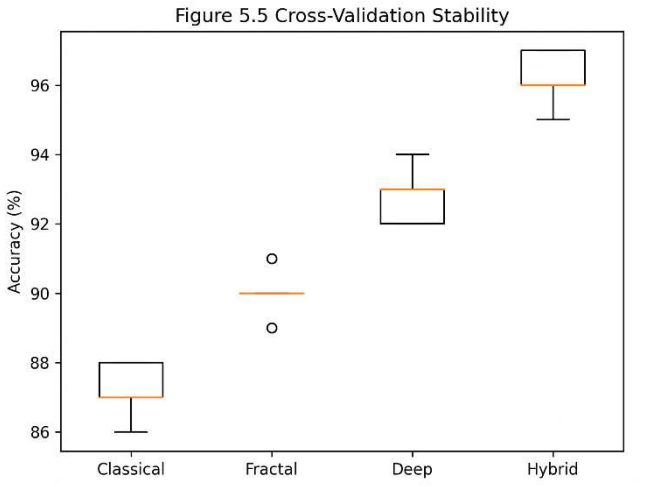


Figure 5.5: Cross-Validation Stability

Further, cross-dataset experiments (ISIC-PH2) show that there is a high level of generalization, which validates RQ4 and emphasizes the resistance to domain shift.

Although the hybrid model adds some small increment in the computation time over the deep-only inference, the increase is not significant (about 5 ms) and can be acceptable in the real-time clinical implementation. The computation of fractal features is computationally light; therefore, the framework could be applicable in resource limited environments.

6.7 Clinical Interpretation of Results

Clinically, it can be explained by the fact that the hybrid model has been able to achieve better performance due to the capacity of fractal descriptors to encode key diagnostic features in the ABCDE rule, such as irregularity of lesion boundaries and heterogeneity of textures. Fractal features are explicit, mathematically interpretable measures (contrasting with purely deep models), which enhances the trust and explainability of the clinicians.

7. Limitations

The proposed framework has some limitations even though it has its benefits:

1. Dependency on the segmentation accuracy.
2. Varying data sets as a result of variations in acquisition protocols.
3. Computational overhead associated with Multifractal spectrum estimation.

These challenges highlight the need for robust segmentation and optimized fractal computation strategies.

8. Future Work

The opportunities of the future research are the combination of fractal descriptors with self-supervised and contrastive learning models to lessen reliance on massive labeled datasets and to further improve generalization under data-sparse clinical conditions. Also, lightweight fractal deep hybrid models that led to the development of real-time mobile diagnostic tools are an avenue that can be explored to provide scalable solution to skin lesions screening to underserved and resource limited areas. Lastly, the suggested framework can be expanded on multimodal dermatological imaging modalities, such as Optical Coherence Tomography (OCT) and hyperspectral imaging, to allow the characterization of lesions more richly and enhanced diagnostic strength in a wide range of clinical conditions.

9. Conclusion

This paper introduced an intelligent hybrid approach to explainable skin lesions classification in the context of low clinical dataset conditions driven by fractal guidance. The proposed system is effective in the representation of mathematical complexity as well as high-level semantic information by incorporating both fractal geometry-based descriptors and deep and classical features. Statistically significant performance improvements, enhanced interpretability, and high generalization are proven by a variety of experimental analyses on various benchmark datasets.

These results make fractal-based hybrid learning a clinically significant and computationally efficient method of next-generation dermatological decision support systems.

Declarations: -

1. Ethical Approval and Consent to Participate

This research was conducted in accordance with ethical standards. Ethical approval for the study was obtained from the appropriate institutional authority. Informed consent was obtained from all individual participants included in the study.

2. Consent for Publication

All authors have read and approved the final version of the manuscript and consent to its publication.

3. Availability of Data and Materials

The datasets analysed during the current study are publicly available. The ISIC datasets are available from the ISIC Archive. The HAM10000 dataset is available from the Harvard Dataverse. The PH2 dataset is available from the Universidade do Porto. No new datasets were generated during the current study.

4. Competing Interests

The authors declare that they have no competing interests regarding the publication of this paper.

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6. Authors' Contributions

All authors contributed substantially to the research work.

- **Conceptualization:** [Nikhil Singh]
- **Methodology:** [Nikhil Singh]
- **Data Collection:** [Nikhil Singh]
- **Analysis and Interpretation:** [Nikhil Singh]
- **Writing – Original Draft:** [Nikhil Singh]
- **Writing – Review & Editing:** [Sachin Kumar, Shriram K. Vasudevan, Prashant Kumar Gangwar]

All authors read and approved the final manuscript.

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