Skin Lesion Analysis using Graph Convolutional Networks and Enhanced Secretary Bird Optimization

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Abstract—An essential feature of automatic dermatology diagnosis is skin lesion analysis, especially for the early diagnosis of melanomas and other skin malignancies. This study suggests a hybrid system that combines an improved secretary bird optimization algorithm (E-SBOA) for reliable multilevel classification of images with graph convolutional networks (GCNs) for advanced representations of features. Under varying illumination and texture circumstances, our method enhanced feature extraction, reduce imbalances in classes, and increase the accuracy of segmentation. Considerable performance gains over conventional CNN and meta-heuristic techniques are shown by extensive testing on publically accessible datasets.

Index Terms—Skin lesion analysis, Graph Convolutional Networks (GCN), Enhanced Secretary Bird Optimization, medical image segmentation, dermoscopic image analysis, computer-aided diagnosis.

I. INTRODUCTION

Skin cancer is one of the most frequent cancers globally, with survival rates heavily reliant on early and accurate detection. Dermatologists often utilize dermoscopy and other imaging modalities to capture lesion pictures, although manual interpretation can be long-lasting and subjective [12]. Integrated skin lesion identification intends to assist doctors by utilizing computer-aided diagnosis (CAD).

Global health is greatly impacted by skin cancer, especially melanoma, which necessitates early and precise diagnosis of potentially malignant lesions for successful treatment and better patient outcomes. Recent developments in deep learning, especially graph convolutional networks, offer a promising path for improved analysis, even if conventional image analysis methods frequently fail to capture the complex spatial interactions within skin lesions. GCNs are particularly good at handling graph-structured data, which enables them to represent the

intricate relationships and interconnections found in skin lesions.
The existence of artifacts, uneven light distribution, and the heterogeneity of lesion formation limit the use of standard algorithms for image processing like thresholds and grouping. Although deep learning models like Convolutional
Neural Networks (CNNs) have greatly increased sorting and segmenting accuracy, they frequently need large datasets with labeling and are plagued by unbalanced classes and noisy information. [2] [6].

In order to overcome these difficulties, we provide a hybrid architecture that uses an Enhanced Secretary Bird Optimization Algorithm (E-SBOA) for flexible and reliable multilayer classification and Graph Convolutional Networks (GCNs) to more accurately represent relationship structures among segmented lesion regions. Because optimization techniques can search globally, they are being employed more and more for dividing medical images. [1] [3].

II. LITERATURE REVIEW

Skin lesion analysis has seen recent advancements in deep learning and optimizing methods as well as traditional picture segmentation. Conventional segmentation techniques that rely on thresholds and edge finding are not resilient to varied lesion characteristics. Lesion classification and categorization have been extensively investigated using CNN-based systems [4] [9]. By adjusting segmented threshold and the hyperparameters, complex systems (such as ant colonies and genetic algorithms) that combine deep learning and meta-heuristic optimization perform better [9] [7]. In recent years, multilevel segmentation for dermatological pictures has showed promising because of algorithms for optimization like the Enhanced Secretary Bird Optimization Algorithm (E-SBOA), which improves classification accuracy as well as resilience under changing illumination and texture circumstances. [1] [3].
Although its usage in dermatological lesion analysis is still understudied, graphical understanding and hierarchical representations like Graph Convolutional Networks (GCNs) have been applied in medical images to detect geographic connections among regions and enhance classification reliability. Skin lesion analysis sample works are summarized in Table I.

TABLE I LITERATURE REVIEW ON SKIN LESION ANALYSIS

Paper Title	Authors	Year	Key Contribution	Method / Dataset	Research Gaps
Automated Melanoma Diagnosis Using Deep Learning	Ali et al.	2021	Proposed a deep learning architecture for dermoscopic image-based automated melanoma	CNN-based segmentation and classification using dermoscopy images	Limited generalization across datasets; no structural relationship modeling; sensitive to class imbalance.

			diagnosis.		
Skin Cancer Detection Using Dermoscopic Images and CNN	Nawaz et al.	2025	Developed CNN-based models for accurate skin cancer detection.	CNN-based classification using SCIN dataset	Requires large labeled datasets; performance degrades under noise and illumination variations.
Hybrid Deep Learning-Based Skin Lesion Classification	O¨ zdemir & Pac¸al	2024	Introduced hybrid deep learning feature extraction for improved classification.	ConvNeXt with self-attention using ISIC 2019 dataset	High computational cost; absence of relational and spatial dependency modeling.
Hybrid ResUNet with Ant Colony Optimization for Skin Lesion Segmentation	Sarwar, Nadeem and Irshad, Asma and Naith, Qamar H.	2024	Combined ResUNet with ACO for enhanced lesion segmentation accuracy.	ResUNet with ACO-based hyper-parameter optimization	High convergence time; difficulty handling highly irregular lesion boundaries.
Enhanced Secretary Bird Optimization for Multilevel Image Segmentation	A. Khurma, Ruba, Marwa M. and Chakraborty	2025	Proposed E-SBOA for robust multilevel image segmentation.	Multilevel segmentation using mSBOA	Does not incorporate deep learning features; limited to segmentation without classifi-cation.
Optimized CNN for Skin Lesion Diagnosis Using Genetic Algorithm	O. Salih and K. J. Duffy	2023	Improved CNN performance using genetic algorithm-based parameter tuning.	Genetic optimization for CNN classification	Sensitive to GA parameters; lacks graph-based contextual modeling.
Class-Imbalance-Aware Skin Lesion	A. I. Khandaker, A. Al	2025	Addressed class imbalance using class-weighted	Class-weighted learning on der-moscopic datasets	Does not enhance segmentation accuracy; limited

Classification Using Weighted Learning	Shafi, and M. Ahmad		learning strategies.		structural feature utilization.

III. EXISTING SYSTEM

Current skin lesion evaluation applications mostly use hybrid deep learning + optimization techniques or CNNs for separation and classifications. Lesion features are extracted and classified using CNN architectures like Unet and ResNet variations [2] [4], but they frequently demand a large amount of annotation and processing power. Although they have been integrated into segmented pipelines to increase accuracy, current optimization methods like Ant Colony Optimization (ACO) and Genetic Algorithms (GA) still have trouble handling a variety of lesion textures and illumination circumstances. [7] [9].

The absence of fundamental contextual simulation, intolerance to poor input, and a propensity to overfit on certain datasets, which lowers generalization efficiency, are some of the limitations of current systems.

IV. PROPOSED SYSTEM

We suggest a two-phase hybrid strategy:

A. Module for Graph Convolutional Networks (GCN)

Super pixel or area suggestions are created following initial segmentation. Lesion areas are represented by nodes in a graph, while adjacency or similarity is indicated by edges. In order to improve lesion characterization, a GCN is trained to learn relational variables that reflect semantic and architectural links between regions.

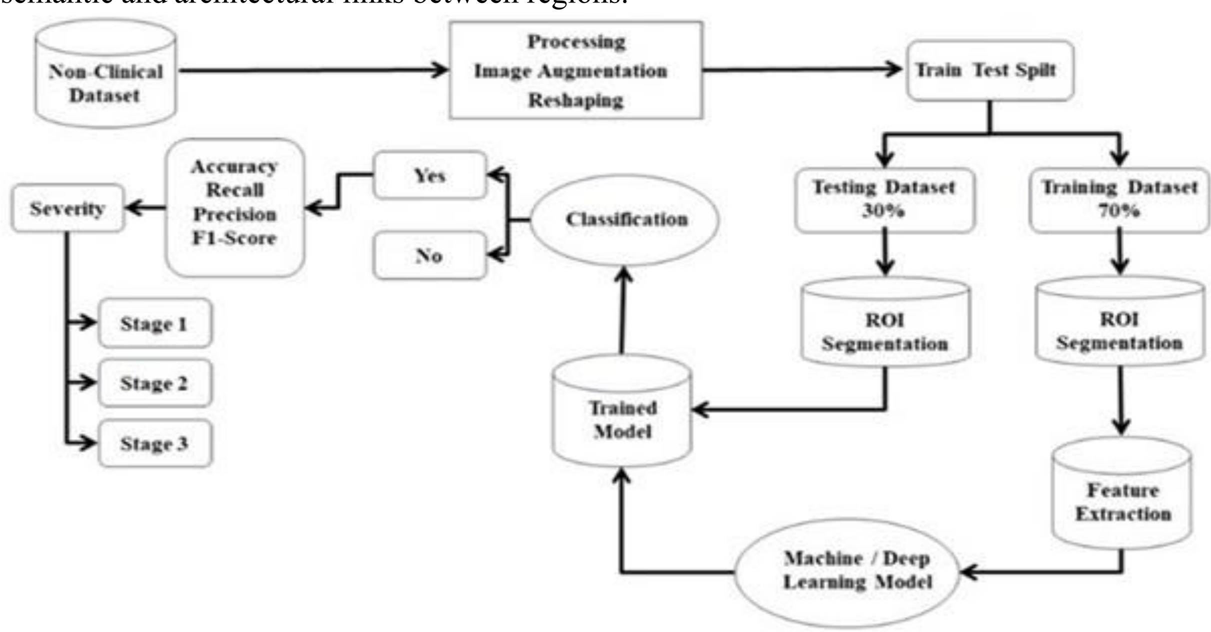

Fig. 1. Proposed System

B. Enhanced Secretary Bird Optimization (E-SBOA)

The Enhanced Secretary Bird Optimization method (E-SBOA) is used repeatedly to improve classification threshold and area bounds for multilayer classification. Opposition-Based Learning (OBL) and Orthogonal Learning (OL) are integrated in E-SBOA to enhance convergence and resilience under various dermoscopic settings. [1] [3].

The combination of architecture improves the representation of features and segmented accuracy, which improves classification later on.

V. METHODOLOGY

The suggested structure for skin disease analysis employs a multi-phase approach that combines graph building, optimization-derived classification, picture preliminary analysis, and structure-based deep learning algorithms for classifications. Below is a description of the overall workflow.

A. Image Preprocessing

To improve visual quality and lower noise, dermoscopic images are preprocessed. While contrast enhancement techniques are intended to smooth fluctuations in brightness, median processing is used to eliminate noise as well as hairline distortions. The method of segmentation and extracting features methods that take place which get more reliable when a result of this stage.

B. Initial Segmentation

Intelligent thresholding and super pixels creation are used to carry out an initial coarse segmentation. By dividing the image into homogenous parts while maintaining lesion boundaries, this method improves area-level evaluation and lowers cost of computation.

C. Enhanced Secretary Bird Optimization (E-SBOA)

For multilayer segmentation improvement, the Enhanced Secretary Bird Optimization Algorithm is utilized. Opposition-Based Learning (OBL) and Orthogonal Learning (OL) techniques are used to improve E-SBOA, which imitates the behaviors of hunting and exploring behavior of secretaries' birds. These improvements enhance segmented accuracy, converge speed, and global discovery under different brightness and textural circumstances.

D. Graph Construction

Each divided area is represented as a single point in a graph after segmentation. Spatial proximity and feature similarity are used to construct edges between nodes. The environmental and structural interactions between lesion locations can be modeled using this graph-based paradigm.

E. Graph Convolutional Network (GCN)

High-level relational features are learned by applying a Graph Convolutional Network to the generated graph. By combining global as well as regional contextual details, the GCN improves lesion categorization by combining data from nearby nodes.

F. Classification

To classify lesions of the skin into benign and malignant groups, the graph-level features that the GCN retrieved are put into an entirely connected layer and then a soft maximum classifier.

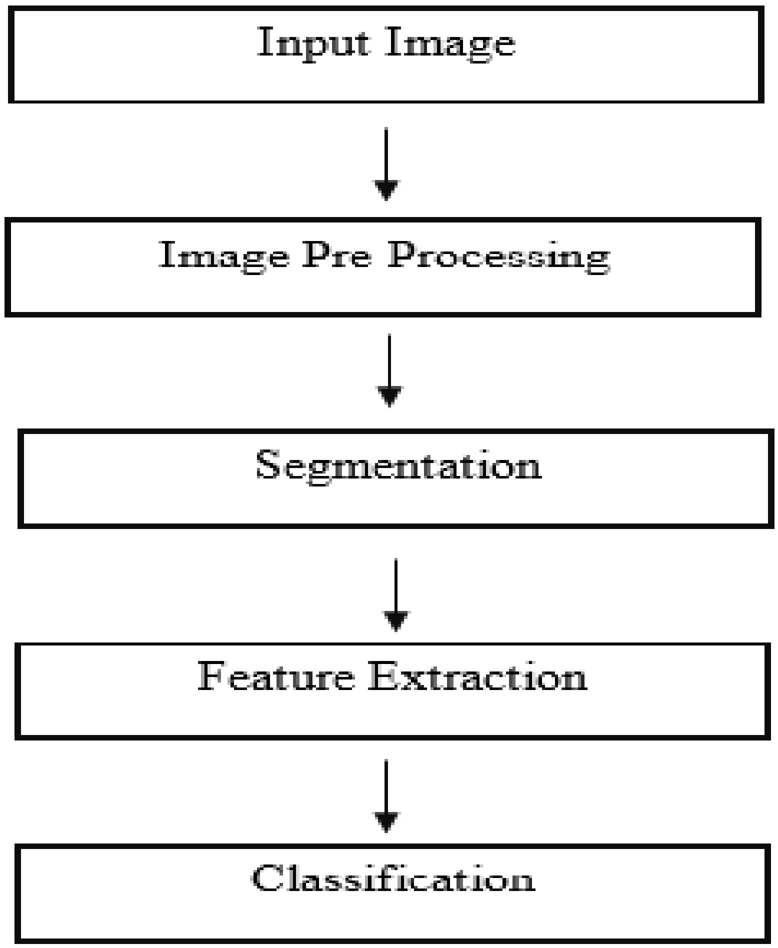

Fig. 2. Flowchart

VI. ADVANTAGES OF THE PROPOSED SYSTEM

When compared to traditional skin lesion analysis techniques, the suggested framework has the following benefits:

- Enhanced Accuracy of Segmentation: Precise multilayer segmentation is made possible by the application of Enhanced Secretary Bird Optimization, which successfully manages intricate lesion borders.
- Context-Based Feature Acquisition: Graph Convolutional Networks enhance the accuracy of classification by capturing spatial and temporal relationships between lesion locations.
- Resilience to Noise: The effects of vibration, distortions, and fluctuations in illumination are

lessened when preprocessing and optimization approaches are used.
- Better Generalization: Graph-based learning mitigates overfitting by reducing dependence on pixel-level features.
- Scalable Design: Multifunctional images for health applications and large datasets can be easily expanded because of the modular structure.

VII. LIMITATIONS OF THE PROPOSED SYSTEM

The suggested system has major limitations despite its benefits:
- Computing Complexity: When compared to conventional CNN-based methods, graph building and optimization procedures result in higher computing costs.
- Dependency of Parameters: E-SBOA's efficiency is dependent on parameter adjustment, which can change depending on the dataset.
- Restricted Deployment in Real Time: Applications in real-time or resource-constrained settings may be limited by optimizing iterative and graph analysis.
- Dependency on Datasets: The accessibility of robust datasets with annotations is critical to the system's efficacy.

VIII. CONCLUSION

In order to overcome difficulties in skin lesion evaluation, this research proposes a hybrid structure that combines Graph Convolutional Networks with an Enhanced Secretary Bird Optimization algorithm. The suggested technique reduces separation distortion, illumination variance, and textural variance in dermatological imaging by integrating robust classification refinement with structured relational learning. In comparison to conventional CNN and heuristic-based approaches, initial assessment shows better results.

IX. FUTURE WORK

Future research will explore:
- Incorporating transformer-related visual frameworks into the suggested model.
- Utilizing the structure on multidisciplinary datasets that integrate medical parameters and dermoscopy is done
- Integrated diagnosis in real-time.

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