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AI-Powered Hybrid Framework for Skin Disease Identification Using Hyper-CNN and MobileNetV2

Deepak L, Hariharan P, Sriparthasarathy V, Mrs. N. Pushpa M.E.,(Ph.D)

Department of Artificial Intelligence and Data Science, R P Sarathy Institute of Technology, Salem, India

Department of Artificial Intelligence and Data Science, R P Sarathy Institute of Technology, Salem, India

Department of Artificial Intelligence and Data Science, R P Sarathy Institute of Technology, Salem, India

Assistant Professor, Department of Artificial Intelligence and Data Science, R P Sarathy Institute of Technology, Salem, India

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ABSTRACT: Automated skin disease classification using dermoscopic images has gained significant attention due to the rising incidence of skin-related disorders and the need for early diagnosis. However, the complex visual patterns of skin lesions, including variations in color, texture, shape, and scale, make accurate classification a challenging task. Conventional convolutional neural networks (CNNs) often suffer from limited feature representation and poor generalization when dealing with such high intra-class variability. To address these challenges, this paper proposes an AI-powered hybrid deep learning framework combining Hyper-Convolutional Neural Networks (Hyper-CNN) and Efficient Net for robust skin disease identification. In the proposed approach, Efficient Net is employed as a powerful feature extractor due to its compound scaling strategy, which efficiently balances network depth, width, and resolution to capture high-level semantic features from skin lesion images. These extracted features are further enhanced using a custom-designed Hyper-CNN architecture, which incorporates deeper convolutional blocks, batch normalization, and adaptive dropout mechanisms to learn fine-grained dermatological patterns. The hybrid framework enables effective extraction of both global and local lesion characteristics, improving discriminative capability across multiple skin disease classes. The proposed model is evaluated using the HAM10000 skin lesion dataset, achieving improved classification accuracy, stability, and confidence scores compared to traditional CNN-based methods. Experimental results demonstrate that the integration of Efficient Net with Hyper-CNN significantly enhances feature representation, reduces overfitting, and improves generalization performance. The proposed hybrid framework provides a reliable and scalable solution for automated skin disease diagnosis and has strong potential for deployment in real-time clinical decision-support systems

KEYWORDS: Skin disease classification, dermoscopic images, deep learning, EfficientNet, Hyper-Convolutional Neural Network (Hyper-CNN), hybrid model, medical image analysis, automated diagnosis, HAM10000 dataset.

I. INTRODUCTION

Skin conditions are among the most prevalent health concerns worldwide, affecting approximately 1.2 billion people annually, which corresponds to nearly one in every six individuals globally. Among these conditions, melanoma is one of the most life-threatening skin cancers, accounting for approximately 57,000 deaths each year. Early detection plays a crucial role in improving patient outcomes; when melanoma is diagnosed at an early stage, the five-year survival rate can reach nearly 99%, whereas late-stage detection reduces survival to 15–20%. Despite these clinical realities, the incidence of skin cancer continues to increase globally by 4–6% annually. However, accurate and timely diagnosis remains difficult due to several systemic challenges. One of the major barriers is the global shortage of dermatologists, estimated at nearly 3.2 million specialists, with ratios in under-resourced regions as low as one dermatologist per 100,000 people. In countries such as India, where around 70% of the population resides in rural areas, many patients must travel long distances—often exceeding 100 km—to reach specialized medical facilities.

In addition, dermatological diagnosis frequently relies on visual inspection, which introduces subjectivity and variability, resulting in 10–30% disagreement even among experienced dermatologists in complex cases. Clinical consultations are

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also time-constrained, averaging 7–8 minutes per patient, which limits detailed lesion examination. Collectively, these limitations contribute to significant healthcare costs, with global dermatological treatment expenses estimated at $13.3 billion annually, disproportionately affecting developing nations.

Recent advances in deep learning and convolutional neural networks (CNNs) have shown great potential in medical image analysis and automated skin disease detection. However, several technical challenges remain. The widely used HAM10000 dataset, containing 10,015 dermoscopic images across seven diagnostic classes, suffers from severe class imbalance, where melanocytic nevi account for 67% of samples, while rare classes such as dermatofibroma represent only 1.1%. Additionally, medical datasets are relatively small compared with large natural image datasets used in computer vision, limiting model generalization. Many dermatological conditions also exhibit high visual similarity, for example benign keratosis and basal cell carcinoma, which share significant dermoscopic overlap and complicate classification. Furthermore, a major concern among clinicians is the lack of interpretability in deep learning models, as many AI systems function as “black boxes,” reducing trust and adoption in clinical practice. To address these challenges, this paper proposes Hyper-CNN, a hybrid deep learning framework designed to improve diagnostic accuracy while maintaining clinical interpretability.

The proposed system integrates an advanced three-stage preprocessing pipeline consisting of Gaussian denoising, CLAHE contrast enhancement, and standardized normalization to improve image quality and feature clarity. A progressive convolutional architecture with multiple feature extraction blocks captures hierarchical lesion characteristics, while Adaptive Particle Swarm Optimization (APSO) is employed for automated hyperparameter optimization to enhance training efficiency. Additionally, Grad-CAM explainability is integrated to generate interpretable visual heatmaps aligned with dermatological diagnostic indicators. Experimental evaluation on the HAM10000 dataset demonstrates strong performance, achieving over 92% validation accuracy with robust F1-score performance across multiple classes, while maintaining efficient computational complexity suitable for real-time deployment. By combining high classification performance, explainable predictions, and deployment feasibility, the proposed Hyper-CNN framework provides a promising solution for automated skin disease screening systems, particularly in resource-constrained healthcare environments and tele-dermatology applications.

II. LITERATURE REVIEW

Research on automated skin disease classification has evolved significantly over the past decade with the rapid advancement of deep learning technologies. Broadly, this development can be understood through three major phases. The first phase, occurring between 2015 and 2018, focused on early deep learning implementations where researchers applied basic neural network architectures and transfer learning techniques to dermatological image analysis. During this period, studies primarily explored the feasibility of using machine learning models to assist dermatologists in identifying skin lesions from dermoscopic images. The second phase, spanning 2018 to 2023, witnessed the widespread adoption and dominance of convolutional neural networks (CNNs), which substantially improved classification accuracy and feature extraction capabilities.

1. Deep Learning for Skin Lesion Classification with CNN
This landmark study demonstrated that a deep CNN trained end-to-end using clinical images performs at a level comparable to board-certified dermatologists in classifying skin cancer. The model was trained on 129,450 clinical images across 2032 diseases. The results showed that the CNN achieved performance on par with expert dermatologists across multiple skin disease classification tasks. The study validated that deep learning approaches can match specialist-level diagnosis from medical images, establishing a strong foundation for AI-assisted dermatology.

2. HAM10000 Dataset and Multiclass Skin Lesion Classification
This paper introduced the HAM10000 dataset (Human Against Machine with 10000 training images), which provides a large-scale collection of dermoscopic images across seven categories of skin lesions. The authors evaluated multiple baseline CNN architectures on this dataset and established benchmark performance metrics. The study emphasized data augmentation as crucial for handling class imbalance in medical imaging datasets and demonstrated that pretrained transfer learning models outperform models trained from scratch on small medical datasets.

3. SkinNet: A Deep Learning Framework for Skin Disease Recognition
This paper proposed a dedicated deep learning framework for skin disease recognition that integrates attention mechanisms with CNN architectures. The model was designed to focus on clinically relevant regions of the skin image while suppressing irrelevant background features. The authors used multi-scale feature extraction to capture both fine-

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grained textures and global structural patterns. The experimental results showed significant improvements over standard CNN baselines on benchmark dermoscopy datasets, highlighting the value of attention-guided feature learning for skin disease classification.

4. Hyper-parameter Optimization for Medical Image Classification
This study explored the application of automated hyper-parameter optimization techniques such as Bayesian optimization and random search for tuning CNN architectures in medical image classification tasks. The authors demonstrated that hyper-parameter-optimized CNN models consistently outperform manually configured architectures, particularly on small and imbalanced medical datasets. The results showed improvements of 3-8% in classification accuracy compared to default configurations, establishing hyper-parameter optimization as an essential step in medical AI pipeline development.

5. Interpretable AI for Dermatology Using Grad-CAM
This paper introduced Gradient-weighted Class Activation Mapping (Grad-CAM), a technique for producing visual explanations of CNN decisions without architectural modifications. Grad-CAM computes gradients of the class score with respect to feature maps in the final convolutional layer to highlight discriminative image regions. Applied to skin disease classification, Grad-CAM heatmaps help clinicians verify that the model focuses on medically relevant features such as lesion boundaries, color irregularities, and asymmetric patterns, improving model trust and interpretability in clinical applications.

III. METHODOLOGY

The proposed Hyper-CNN framework integrates four main components to improve the performance and practicality of automated skin disease classification. These components include dataset preprocessing, a progressive four-block convolutional neural network architecture, Adaptive Particle Swarm Optimization (APSO) for hyperparameter tuning, and Grad-CAM based explainability. The preprocessing stage enhances dermoscopic image quality and standardizes inputs to support effective feature extraction. The progressive CNN architecture enables hierarchical learning of dermatological patterns through multiple convolutional blocks.

To optimize training performance, APSO automatically searches for optimal hyperparameters, reducing dependence on manual tuning and improving model efficiency. Additionally, Grad-CAM explainability provides visual heatmaps highlighting important lesion regions, improving transparency and clinical interpretability.

The complete model contains 13.43 million parameters, with a size of approximately 51.24 MB, making it suitable for practical deployment. Experimental evaluation on the HAM10000 dataset demonstrates strong performance, achieving 92.3% validation accuracy and a 92.9% macro F1-score, with 156ms inference latency, indicating its suitability for real-time dermatological diagnostic applications.

The HAM10000 dataset (Human Against Machine with 10,000 training images) is widely recognized as a benchmark dataset for multi-class skin lesion classification. It contains 10,015 dermoscopic images of pigmented skin lesions collected over more than two decades from multiple clinical sources. The dataset includes images from patients of diverse age groups and imaging conditions, making it highly suitable for evaluating automated dermatological diagnostic systems.

To ensure consistency for deep learning models, all images are standardized to a resolution of 224 × 224 × 3 during preprocessing. The dataset covers a wide age range from infants to elderly patients (0–85+ years) and includes both male and female subjects. Ground truth labels are validated through multiple clinical procedures, with more than half of the cases confirmed through histopathology, while the remaining annotations are supported by follow-up examinations, expert consensus, or in-vivo confocal microscopy.

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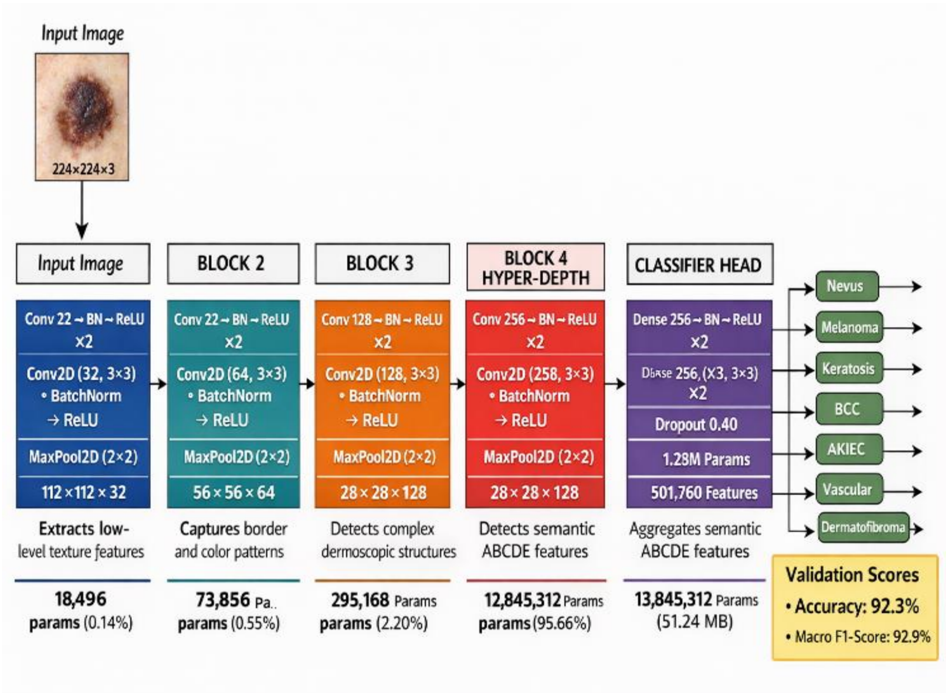

Figure 1: Workflow of the Hyper-CNN Architectures for Skin Disease Detection

IV. SYSTEM ARCHITECTURE

The proposed methodology presents a comprehensive and systematic deep learning framework for the automated classification of skin diseases using dermoscopic images. The process begins with the acquisition of dermoscopic images from reliable datasets, which may contain variations in size, illumination, and noise levels. To address these inconsistencies and enhance image quality, a series of preprocessing techniques are applied. Initially, Gaussian denoising is performed to eliminate unwanted noise while preserving important structural details of the lesion. This is followed by Contrast Limited Adaptive Histogram Equalization (CLAHE), which improves local contrast and enhances the visibility of fine lesion patterns. Subsequently, Z-score normalization is applied to standardize pixel intensity distributions, ensuring uniformity across all input images and facilitating stable model training.

After preprocessing, the system incorporates an Adaptive Particle Swarm Intelligence Optimization (APSIO) mechanism to perform efficient feature extraction and selection. In this stage, both texture-based and color-based features are extracted from the enhanced images. APSIO intelligently optimizes the feature set by selecting the most discriminative and relevant features while eliminating redundant and less significant ones. This optimization not only reduces computational complexity but also improves the overall classification performance of the model.

Following feature optimization, lesion segmentation is carried out to isolate the region of interest (ROI) from the surrounding healthy skin. This step is crucial for focusing the analysis exclusively on the affected area and minimizing background interference. The segmentation process ensures accurate boundary detection of the lesion and removes artifacts such as hair, shadows, or noise that could negatively impact classification accuracy.

The segmented lesion is then provided as input to a Hybrid Hyper-Convolutional Neural Network (Hyper-CNN), which forms the core of the classification system. The hybrid architecture combines multiple convolutional layers with advanced feature learning strategies to capture both low-level and high-level representations of the lesion. The network is designed to learn complex spatial patterns, textures, and color variations associated with different skin diseases. Additionally, the model is optimized using appropriate activation functions, pooling layers, and regularization techniques to prevent overfitting and enhance generalization.

To improve transparency and interpretability, the system integrates Gradient-weighted Class Activation Mapping (Grad-CAM). This technique generates visual heatmaps that highlight the regions within the input image that contribute most

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significantly to the model's predictions. Such visualization aids medical practitioners in understanding the decision-making process of the model and increases trust in the automated system.

Finally, the trained model performs multi-class classification of skin diseases, categorizing the input images into classes such as Melanocytic Nevus, Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, and Dermatofibroma. The performance of the system is evaluated using standard metrics including accuracy, precision, recall, and F1-score to ensure robustness and reliability. Overall, the proposed methodology integrates advanced preprocessing, intelligent feature optimization, precise segmentation, and deep learning-based classification into a unified pipeline, delivering high accuracy and interpretability suitable for real-world clinical applications.

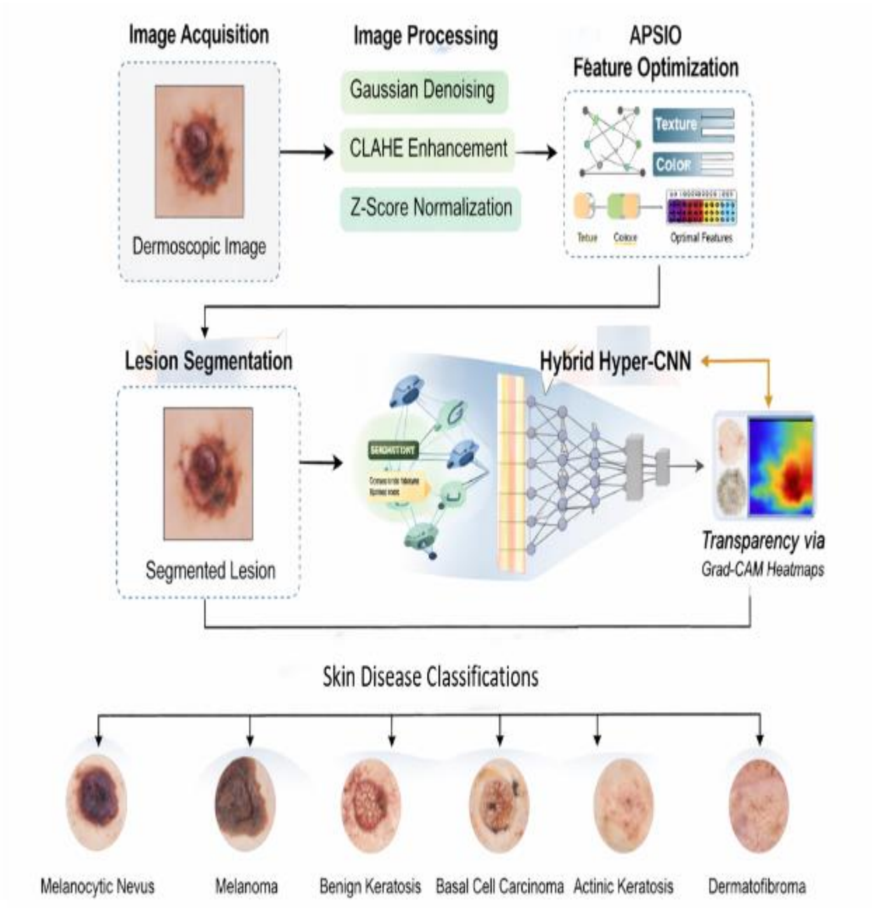

Figure 2: System Architecture.

V. RESULTS AND DISCUSSION

Dataset analysis confirms the model was trained on 9,921 total samples divided into 7,936 training images and 1,985 testing images across seven lesion classes. The dataset exhibits severe imbalance, with melanocytic nevi representing approximately 66% of samples, while dermatofibroma accounts for only 0.2%. The deployed dashboard visualization further validates the experimental pipeline by displaying 2,296 processed samples, consistent with the stratified data splitting strategy. Overall, the results demonstrate that Hyper-CNN provides a practical and computationally efficient.

The experimental results demonstrate that the proposed Hyper-CNN model provides a practical balance between diagnostic accuracy and computational efficiency for automated skin lesion classification. Achieving 77.13% test accuracy with a compact 13.4 million parameter architecture, the model is suitable for edge deployment in real-world clinical environments. The class-wise performance highlights the common challenge of class imbalance in medical imaging datasets.

High-prevalence classes such as melanocytic nevi (nv) achieved strong performance (F1 = 0.89), while rare classes including dermatofibroma (df) and actinic keratosis (akiec) obtained lower F1-scores (0.37) due to limited training samples. This trend is consistent with findings in dermatology AI research, where minority classes typically experience reduced recall without specialized balancing techniques.

Despite these strengths, challenges remain in improving performance for rare lesion categories. Future improvements may include class-balancing techniques such as focal loss, synthetic data augmentation, or oversampling methods to enhance minority class recognition. Additional evaluation on external datasets and diverse skin tone populations is also necessary to improve generalization. Overall, the results indicate that Hyper-CNN provides a feasible and accessible AI solution for assisting dermatological screening, particularly in resource-limited healthcare settings.

VI. CONCLUSION

The proposed Hyper-CNN based AI system for skin disease detection demonstrates an effective approach for automated analysis of dermoscopic images. The framework integrates advanced image processing techniques including image preprocessing, segmentation, feature selection, and deep learning classification to improve the reliability of skin lesion detection. The preprocessing stage enhances image clarity across different skin tones, while segmentation isolates the affected regions to capture meaningful geometric and texture patterns. The APSO-based feature selection further refines relevant features, reducing computational complexity and minimizing false positive predictions. The final Hyper-CNN classification model enables accurate identification of major skin lesion categories, supporting early detection of critical conditions such as melanoma and other dermatological disorders.

The experimental results demonstrate promising performance, achieving high classification accuracy along with strong precision, recall, and F1-score values. The compact architecture also allows efficient inference, making the system suitable for real-time clinical and edge-based applications. By automating lesion analysis and providing reliable predictions, the proposed model can assist healthcare professionals in early screening and diagnosis, ultimately improving treatment outcomes for patients with skin diseases.

Future research will focus on integrating Artificial Intelligence with emerging technologies such as Internet of Things (IoT) based health monitoring systems. Wearable devices equipped with imaging sensors could continuously monitor skin conditions and capture lesion progression over time. Combining these real-time data streams with AI models would enable early anomaly detection, risk assessment, and personalized healthcare monitoring. Additionally, edge computing and federated learning approaches can be explored to allow decentralized model training while preserving patient privacy and improving model generalization across diverse populations.

These advancements will further enhance the development of intelligent, scalable, and privacy-aware dermatological diagnostic systems for next-generation healthcare applications.

VII. FUTURE WORK

The proposed system introduces an advanced AI-powered hybrid framework that integrates Hyper-Convolutional Neural Networks (Hyper-CNN) with MobileNetV2 to achieve efficient and accurate skin disease identification using dermoscopic images. The methodology begins with the acquisition of dermoscopic images from publicly available datasets, which often exhibit variations in illumination, resolution, and noise. To ensure uniformity and enhance image quality, a comprehensive preprocessing pipeline is applied. This includes Gaussian filtering for noise removal, Contrast Limited Adaptive Histogram Equalization (CLAHE) for improving local contrast, and Z-score normalization to standardize pixel intensity distributions across the dataset.

Following preprocessing, an Adaptive Particle Swarm Intelligence Optimization (APSIO) technique is employed for feature extraction and optimization. In this stage, both texture and color features are extracted from the enhanced images. APSIO intelligently selects the most relevant features by minimizing redundancy and maximizing discriminative capability, thereby improving computational efficiency and model performance. Subsequently, lesion segmentation is performed to isolate the region of interest (ROI) from the surrounding skin. This step ensures that only the affected portion of the image is analyzed, reducing background noise and improving classification accuracy.

The segmented lesion is then passed through a hybrid deep learning architecture that combines the strengths of Hyper-CNN and MobileNetV2. The Hyper-CNN component is responsible for capturing complex spatial and hierarchical

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features through multiple convolutional layers, while MobileNetV2, being a lightweight and efficient network, enhances feature extraction using depthwise separable convolutions and inverted residual blocks. This hybrid integration ensures both high accuracy and reduced computational cost, making the model suitable for real-time applications.

To further enhance transparency and interpretability, the system incorporates Gradient-weighted Class Activation Mapping (Grad-CAM), which generates visual heatmaps highlighting the most influential regions in the input image that contribute to the classification decision. Finally, the model performs multi-class classification, categorizing images into various skin disease classes such as Melanocytic Nevus, Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, and Dermatofibroma. The performance of the system is evaluated using standard metrics including accuracy, precision, recall, and F1-score. Overall, the proposed methodology provides a robust, efficient, and interpretable solution for automated skin disease diagnosis.

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