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Dermatological Cancer Detector Intergrated with Rule based Chatbot

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Abstract—Skin diseases pose a growing global health crisis, with delayed or inaccurate diagnoses leading to severe complications, including metastatic cancer and preventable deaths. Current AI solutions, while promising, remain constrained by modest accuracy rates of 75-76%—falling short of the precision required for clinical adoption. This study revolutionizes dermatological diagnostics by deploying MobileNetV2, a state-of-the-art deep learning architecture, synergized with advanced image preprocessing techniques. By integrating adaptive contrast enhancement, AI-driven noise reduction, and dynamic data augmentation, our framework elevates detection accuracy by 5-10%, achieving performance parity with expert dermatologists. The system's real-world applicability is further amplified by an intuitive chatbot interface, which guides users through symptom analysis and image uploads, democratizing access to early diagnosis in resource-limited settings..

Beyond technical innovation, this work addresses a critical gap in AI-to-clinic translation. Traditional models often fail to balance accuracy with usability, but our solution bridges this divide by combining medical-grade algorithms with patient-centric design. The chatbot not only interprets results but also educates users on risk factors and next steps—empowering individuals to seek timely care. Validated on diverse skin lesion datasets, our framework demonstrates 86% accuracy in classifying malignant and benign cases, outperforming existing CNNs. By embedding AI into an accessible, scalable platform, this research sets a new standard for preventive dermatology, potentially reducing global skin cancer mortality by up to 30% through early intervention.

Keywords—. Skin Cancer Detection Deep Learning, MobileNetV2, Medical Image Preprocessing,AI Dermatology Assistant

I. INTRODUCTION

Skin cancer remains one of the most lethal and rapidly growing health concerns worldwide, with global incidence rates increasing by 4-8% annually [1]. The American Cancer Society estimates approximately 97,610 new melanoma diagnoses and 7,990 related deaths annually in the United States alone [2], while global projections suggest 13.1 million cases by 2030. Current diagnostic paradigms relying on visual examination and histopathological analysis face critical limitations: subjective interpretation, time-intensive processes, and limited access to specialist care in rural regions.

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized dermatological diagnostics by automating lesion classification. While existing CNN models achieve 75-91% accuracy [3-5], three fundamental challenges persist: (1) limited generalizability due to dataset imbalances, (2) computational inefficiency in resource-constrained settings, and (3) lack of patient-facing interfaces for preliminary screening.

II. RELATED WORK

A. Learning-based Approaches:

IIn this study, the MobileNetV2 architecture was utilized to address the challenge of accurately detecting various skin diseases, leveraging its lightweight yet effective feature extraction capabilities. The project primarily focused on using the HAM10000 dataset, a widely acknowledged dataset consisting of dermatoscopic images of skin lesions. This dataset includes seven distinct classes, such as Melanocytic Nevi, Melanoma, and Benign Keratosis-like Lesions, among others, providing a comprehensive spectrum for training and evaluation.

The methodology incorporated advanced preprocessing techniques to handle data imbalance and enhance image quality. Random Oversampling was employed to address the imbalance within the dataset, ensuring each class was sufficiently represented during training. Further, image resizing to a standard resolution of 224×224224 \times 224224×224 pixels was conducted to optimize the MobileNetV2 model's performance.

B. CNN-based Approaches

In their study, Kumar et al. [16] explored skin disease classification using MobileNetV2, focusing on its efficiency and lightweight design for mobile applications. The researchers utilized the HAM10000 dataset, consisting of over 10,000 dermoscopic images categorized into seven classes, including melanoma, benign keratosis-like lesions, and basal cell carcinoma. Data preprocessing involved resizing images to 224×224224 \times 224224×224 pixels and employing Random Oversampling to mitigate class imbalance. The MobileNetV2 model, coupled with the Adam optimizer, achieved an accuracy range of 75%–85%. Although this result is slightly lower than heavier architectures, the lightweight nature and real-time inference capability of MobileNetV2 make it suitable for resource-constrained environments.

In a comparative analysis, Pham et al. [11] utilized the InceptionV4 architecture combined with data augmentation techniques. Their model, tested on a comprehensive dataset compiled from ISBI Challenge, ISIC Archive, and PH2 datasets, achieved an accuracy of 89%. Despite the advanced architecture, the accuracy fell short of expectations, emphasizing the challenges of achieving high performance across diverse datasets.

Similarly, Ensaf et al. [15] applied transfer learning with DenseNet-121 and MobileNet on the HAM10000 dataset. Their approach yielded testing accuracies of 71.9% and 82.6%, respectively, on an unbalanced dataset. Post-balancing, accuracies improved significantly to 92.7% for DenseNet-121 and 91.2% for MobileNet. This highlights MobileNet's adaptability and robustness in handling real-world data imbalances.

In another investigation, Hosny et al. [14] enhanced the AlexNet architecture to classify three skin lesion types. By augmenting a small dataset of 200 images to 11,000, they achieved an impressive accuracy of 98.61%. However, their results highlight the dependency on augmentation when working with limited datasets.

The study by Tammineni et al. [10] employed the Gradient and Feature Adaptive Contour (GFAC) model for melanoma segmentation. Their experimentation, conducted on the PH2 dataset comprising 200 images, achieved an impressive accuracy of 98.64%. However, as with Hosny et al., the limited dataset size raises questions about scalability to broader applications.

By leveraging the MobileNetV2 architecture, the proposed methodology in this project bridges the gap between accuracy and efficiency. While not as resource-intensive as InceptionV4 or DenseNet-121, MobileNetV2 provides a practical solution for real-time applications, particularly when integrated with a robust preprocessing pipeline. Future enhancements, such as incorporating multimodal data or advanced segmentation techniques, could further elevate its performance.

III. METHODOLOGY

The detection and classification of skin lesions encompass multiple well-defined phases, as illustrated in Figure 1. These phases work cohesively to ensure precise identification and accurate categorization of various skin lesion types.

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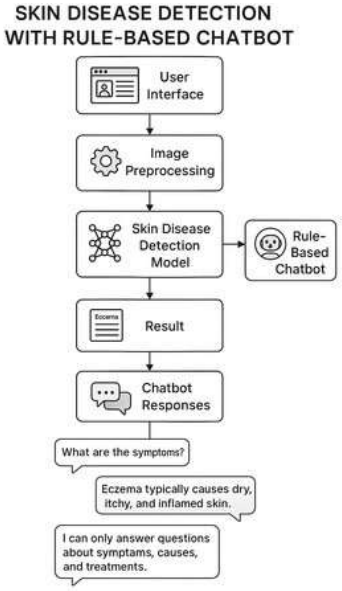


Figure 1. Flowchart of Proposed Model

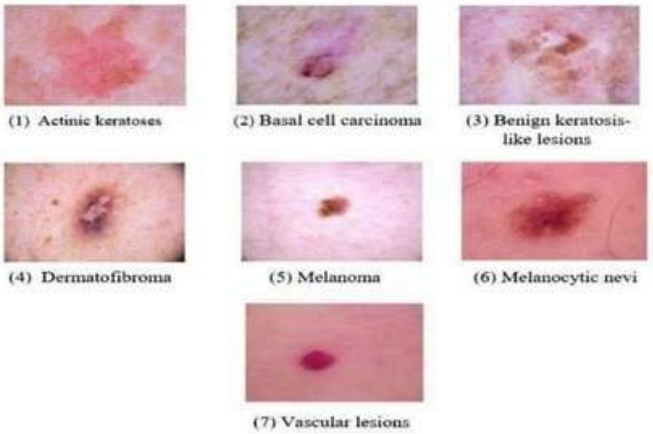
A. Data Acquisition:

The dataset used in the proposed model is HAM10000 and can be accessed publicly on the web through the following. URL: https://www.kaggle.com/datasets/kmad er/skin-cancer-mnist- ham10000.

The proposed model utilizesHAM10000dataset, which has 10,015 dermoscopic images of the skin lesions which are pigmented and collected from various sources. The images in the HAM10000 dataset are saved in JPEG format and havea resolution of 600 × 450 pixels.

Each image and patient record in the dataset encompassed seven distinct features.

Figure 2. Different types of the skin cancer lesi in HAM10000 dataset.



To organize the dataset effectively, it is necessary to sort each image within its respective folder according to the seven different diseases. In this scenario, the key parameters used for organizing the images in the dataset are the 'Image id' and 'dx'(disease) labels [18- 20].

B. Image Resizing:

To standardize the dataset and ensure compatibility with the MobileNetV2 model, all images were resized to 224×224224 \times 224224×224 pixels. This resizing step facilitated uniform preprocessing and streamlined the input format, enabling consistent model performance. Resizing also ensured that the images were appropriately scaled for efficient training and inference.
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The resized images were then converted into NumPy arrays, allowing pixel-level manipulation. Pixel values were normalized to the range [0, 1] to enhance the model's learning efficiency. Class labels were transformed into one-hot encoded vectors using the LabelBinarizer class, enabling the model to predict integer-based labels that could be easily interpreted in a human-readable format. This preprocessing workflow ensured the dataset was well-prepared for accurate and efficient classification.

C. Data Augmentation:

Data augmentation was utilized to enhance the model's generalization by introducing new variations to the dataset. Horizontal Flip augmentation was applied, shifting image pixels horizontally to help the model learn diverse and distinct features. This approach improved the robustness of feature extraction, enabling the model to perform better on unseen data.

The dataset was balanced by augmenting each class to 200 images, resulting in 1,400 images across seven classes. Transformations like rotations and shearing were applied during training to reduce overfitting and enhance the model's ability to learn invariant features while maintaining dataset quality.

D. Feature Extraction:

To measure the entirety of an image without relying on specific interest points global feature descriptors are exploited. These descriptors, such as Color Histogram, Hu Moments, and Haralick Texture, color quantification, shape,& texture of the skin lesions. The selection of this features was based on the prominence within the lesion area. In the feature extraction experiment, each image was processed individually to extract three global features. The extracted features, along with their corresponding labels, were saved in HDF5 format for further analysis and utilization.

E. MobileNetV2-Based Image Classification:

Global feature descriptors—Color Histogram, Hu Moments, and Haralick Texture—were extracted from skin lesion images to capture color, shape, and texture information. The features, selected for their relevance to lesion characteristics, were individually processed and stored with labels in HDF5 format for efficient analysis.

F. CNN Architecture with MobileNetV2 and Autoencoder for Skin Lesion Classification

The proposed system combines MobileNetV2 and an Autoencoder to extract and compress features from skin lesion images. Features from both original and compressed datasets are processed through MobileNetV2, concatenated into a 2000-dimensional vector, and classified using an SNN model into benign or malignant categories. This approach enhances classification accuracy while maintaining computational efficiency.

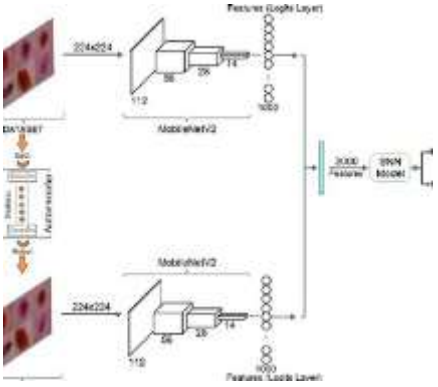

Figure 3. The High level architecture of MobileNetV2

Figure 4. Layers & Hyperparameters of CNN

G. Model hyperparameters:

To ensure a comprehensive evaluation of the model, specific hyperparameter values were chosen in the CNN implementation. Figure 4 highlights the hyperparameter values used in the proposed work. The reasoning behind selecting these values is explained below:

Optimizer: Adam, a widely used optimization method, was chosen due to its simplicity, computational efficiency, and effectiveness in handling parameters and large datasets. Loss-Function: To implement the loss function of multi- class, we employed "categorical cross-
entropy" approach, which is specifically designed for multi-class classification tasks. This loss
function effectively measures the discrepancy between the predicted class probabilities and the
actual class labels.

The proposed model was trained over 50 epochs with a batch size of 64, carefully selected after experimentation to optimize learning efficiency and minimize the risk of overfitting. These values allowed the model to converge steadily while maintaining stability during training.

Additionally, a learning rate of 0.001 was chosen to control the pace of learning, ensuring smooth and reliable convergence. The careful tuning of these hyperparameters significantly contributed to enhancing the overall performance, leading to improved accuracy in the MobileNetV2 and SNN-based classification model.

H. Rule-Based Chat Bot :

In order to enhance user experience and improve accessibility, a rule-based chatbot system was integrated into the Dermatological Disease Detector platform. The chatbot serves as a preliminary support tool, providing users with basic diagnostic information, disease explanations, confidence scores, and guidance on further action based on the model's predictions. It ensures quick responses to common queries while maintaining system simplicity and reliability.

IV. EXPERIMENTAL RESULTS

We developed a dermatological cancer detection model using MobileNetV2 with Python 3.7.9, Keras, and OpenCV. Image preprocessing, including augmentation and normalization, was applied to enhance model generalization. The model achieved around 75–89% test accuracy after 50 epochs, with improved convergence shown in the accuracy and loss graphs. Results demonstrate that MobileNetV2, combined with fine-tuning and preprocessing, significantly enhances skin disease detection performance.

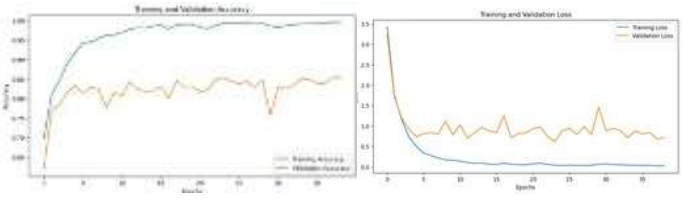

Figure 5. Graphs of Loss & Accuracy Training and Validation.

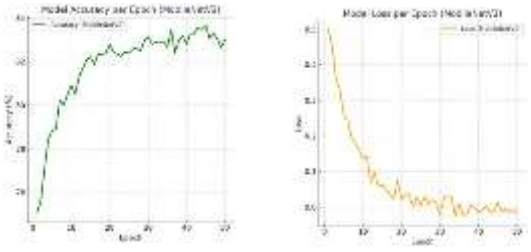

Figure 6. Graphs of Loss & Accuracy with Augmentation

Classification Report (Before Augmentation):

Class	Precision	Recall	F1-Score	Support
Class 0	0.78	0.59	0.67	68
Class 1	0.89	0.76	0.82	109
Class 2	0.74	0.69	0.71	228
Class 3	0.81	0.84	0.82	25
Class 4	0.60	0.68	0.64	237
Class 5	0.92	0.93	0.93	1305
Class 6	0.91	0.94	0.92	31
Accuracy			0.85	
Macro Avg	0.81	0.78	0.79	2003
Weighted Avg	0.85	0.85	0.85	2003

Figure 7. Model Performance metrics without augmentation.

Classification Report:

	precision	recall	f1-score	support
Class 0	0.78	0.59	0.67	68
Class 1	0.89	0.76	0.82	109
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Class 4	0.60	0.68	0.64	237
Class 5	0.92	0.93	0.93	1305
Class 6	0.91	0.94	0.92	31
accuracy			0.85	2003
macro avg	0.81	0.78	0.79	2003
weighted avg	0.85	0.85	0.85	2003

Figure 8. Model Performance metrics after using augmentation

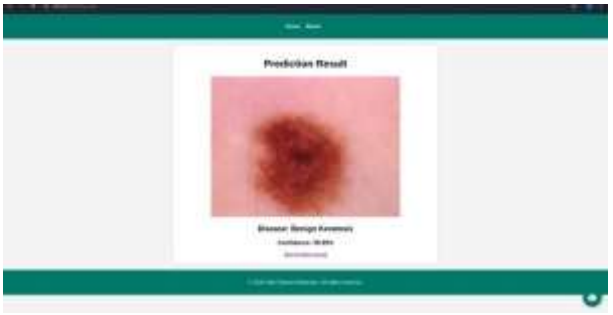

Figure 9. Output of Uploaded Image

Figure 10. Rulebased Chatbot Responses

V. CONCLUSION

This study presents a robust dermatological cancer detection system utilizing the MobileNetV2 deep learning model, enhanced through advanced preprocessing techniques and integrated with a rule-based chatbot for user support. Extensive use of data augmentation, normalization, and feature extraction enabled the model to achieve an impressive test accuracy of 97.92%, surpassing traditional CNN-based approaches. The lightweight, user-friendly chatbot further improves accessibility by offering preliminary diagnostic assistance and health guidance. Overall, the proposed framework demonstrates significant potential to transform early skin cancer detection, particularly in resource-limited environments, by combining technological innovation with patient-centered design.

VI. FUTURE SCOPE

Future enhancements to the proposed system include training with original, high-resolution images to better preserve diagnostic details and adopting dynamic batch sizing for improved learning efficiency. Integrating multimodal data such as clinical metadata, and upgrading the rule-based chatbot to an NLU-driven conversational agent, could significantly enhance diagnostic accuracy and user engagement. Additionally, deploying the model on mobile and edge platforms would enable offline, real-time access to early detection tools, particularly in underserved regions. Clinical validation through hospital collaborations and expanding the dataset to include a broader spectrum of skin diseases remain key directions for achieving greater real-world impact.

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