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MAHATVAK CHIKITSA- AUTOMATED SKIN ONCOLOGY DIAGNOSIS WITH CLINICAL DECISION SUPPORT

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Abstract: Skin cancer is one of the major dermatological conditions where early identification of suspicious skin lesions can assist in timely clinical assessment. However, distinguishing different lesion types from dermoscopic images is challenging because several categories may exhibit similar visual characteristics. This project presents a deep learning-based approach for automated skin lesion classification using dermoscopic images obtained from the International Skin Imaging Collaboration (ISIC) dataset. The proposed system performs image preprocessing, resizing, normalization, augmentation, and class balancing to prepare the dataset for model development. Five transfer-learning architectures, namely VGG19, VGG16, ResNet50, MobileNet, and EfficientNet, are trained and evaluated for the classification of nine skin lesion categories. The models are compared using classification performance measures including accuracy, precision, recall, and F1-score. Among the evaluated architectures, EfficientNet achieves the highest performance with a test accuracy of 90.11% and a macro F1-score of 90.57%. The selected model is further integrated into a Flask-based web application that allows users to upload a dermoscopic image and receive the predicted lesion category, confidence level, and preliminary guidance. The developed system is intended to support computer-aided screening and decision-making, while final diagnosis and treatment decisions remain with qualified healthcare professionals.

Index Terms: Skin Cancer Detection, Skin Lesion Classification, Deep Learning, Transfer Learning, ISIC Dataset, Dermoscopic Images, EfficientNet, Flask.

I. INTRODUCTION

Skin cancer remains one of the most widespread dermatological challenges today, encompassing a wide spectrum of both benign and malignant skin lesions. Timely identification of suspicious lesions is critical—catching a high-risk lesion early can drastically improve patient outcomes and simplify treatment. However, accurately distinguishing between skin lesion types from dermoscopic images is notoriously challenging. Many distinct conditions share subtle visual cues, such as similar colors, borders, and textures, leading to high inter-class ambiguity. Traditionally, diagnosis relies almost entirely on the visual expertise and clinical intuition of trained dermatologists. In resource-limited or remote areas where specialist access is scarce, this reliance creates a significant bottleneck in primary screening.

Recent breakthroughs in Artificial Intelligence (AI) and deep learning present a promising path toward automated, scalable skin lesion analysis. Deep neural networks excel at extracting intricate spatial patterns from complex medical imagery. To maximize diagnostic accuracy without training models entirely from scratch, transfer learning offers a practical solution. By fine-tuning established pretrained architectures—such as VGG16, VGG19, ResNet50, MobileNet, and EfficientNet—models can effectively transfer existing feature-recognition capabilities to specialized medical classification tasks.

To address these diagnostic challenges, we developed MAHATVAK CHIKITSA, a web-based platform for automated skin lesion classification and preliminary clinical decision support. Trained on dermoscopic images sourced from the International Skin Imaging Collaboration (ISIC) dataset, our pipeline incorporates custom preprocessing and data augmentation strategies to handle real-world image variability across nine distinct lesion categories. Comparative evaluation across multiple deep learning architectures showed that EfficientNet achieved the superior performance, reaching a peak test accuracy of 90.11%.

The optimized EfficientNet model was subsequently integrated into a lightweight Flask web application. Through a simple interface, users can upload a dermoscopic image to obtain a predicted lesion category, model confidence score, and tailored preliminary treatment guidance. Designed primarily as an assistive screening tool, MAHATVAK CHIKITSA

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aims to augment primary healthcare workflows—with final clinical diagnoses and therapeutic interventions strictly reserved for certified dermatologists.

Problem statement. Images *objectives* of the project behind this paper are to (i) Develop an automated vision system to detect and categorize diverse skin conditions using standardized dermoscopic photographs., (ii) Benchmark multiple deep learning architectures to evaluate diagnostic accuracy and identify the optimal model for feature extraction and classification., (iii) Implement uncertainty estimation and practical care insights by displaying confidence scores alongside basic non-prescriptive management advice for predicted conditions (iv) Design an accessible web platform that enables users and practitioners to run rapid preliminary checks on suspicious skin marks.

The contributions are: (1) Developed MAHATVAK CHIKITSA, a web-based application designed to identify skin lesions and provide preliminary treatment guidance; (2) Prepared the ISIC dermoscopic images using suitable preprocessing, normalization, and augmentation methods before model training; (3) Trained and compared five deep learning architectures: VGG19, VGG16, ResNet50, MobileNet, and EfficientNet.(4) Tested the models across nine skin lesion classes using performance measures such as accuracy, precision, recall, and F1-score. EfficientNet gave the highest test accuracy of 90.11% among the models evaluated in this study.

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II. BACKGROUND

A. Skin Lesion Classification

A skin lesion classification involves identifying the category of a lesion from its image. This project considers nine categories: actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular lesion.

B. ISIC Dermoscopic Datase

The International Skin Imaging Collaboration (ISIC) dataset provides labelled dermoscopic images for skin lesion analysis. In this project, these images are used for supervised training and evaluation of the deep learning models.

C. Image Preprocessing

The images are resized to 224 × 224 pixels and their pixel values are normalized between 0 and 1. Image augmentation is also applied using operations such as rotation, flipping, zooming, cropping, brightness changes, and colour variation. The training data is balanced to 2,500 images for each class.

D. Transfer Learning Models

Transfer learning is used to apply pretrained deep learning architectures to the skin lesion classification task. The project evaluates VGG19, VGG16, ResNet50, MobileNet, and EfficientNet and compares their classification performance.

E. Computer-Aided Skin Lesion Analysis

The selected classification model is integrated into a Flask-based web application. The application allows an image to be uploaded and provides the predicted lesion category, confidence information, and preliminary treatment-related guidance. The system is designed as a supporting tool and does not replace professional medical diagnosis.

III. LITERATURE SURVEY

Skin Cancer Classification Using Deep Learning

H. L. Gururaj et al. proposed DeepSkin, a deep-learning approach for skin-cancer classification using the HAM10000 dataset. The study used preprocessing techniques such as sampling, DullRazor processing, and segmentation, followed by DenseNet169 and ResNet50 transfer-learning models.

Advantages

- Uses a large publicly available skin-lesion dataset.
- Uses transfer learning to improve classification performance.
- ResNet50 and DenseNet169 can extract complex image features.

Disadvantages

- Mainly focuses on classification and does not provide a complete treatment-guidance module.
- The approach depends on the quality and distribution of the training dataset.
- Multiple preprocessing steps can increase system complexity.



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How this study addresses it:
The Mahatvak Chikitsa system extends the classification workflow by combining image preprocessing with multiple deep-learning models, including VGG16, VGG19, ResNet50, and EfficientNet. The system performs classification and further provides a treatment recommendation module.

GAN Data Augmentation

Q. Su et al. proposed STGAN, a two-stage GAN-based method to generate additional skin lesion images and address the problem of class imbalance in the HAM10000 dataset. The study reported improvements in generated-image quality and classification performance.

Advantages

- Addresses the problem of class imbalance.
- Generates additional synthetic training images.
- Improves classification performance on minority classes.

Disadvantages

- GAN-based image generation increases computational complexity.
- Generated images may not always represent real clinical variations.
- Training GANs can be difficult and time consuming.

How this study addresses it:
This study uses image augmentation during preprocessing to increase variation in the training data while keeping the classification pipeline comparatively straightforward. This helps improve the model's ability to handle variations in skin images without making GAN based image generation the main component of the system.

IncepX Transfer Learning

S. Chatterjee et al. proposed IncepX Ensemble, combining InceptionV3 and Xception for multiclass skin-lesion classification. The study specifically addressed problems such as class imbalance and reported 98% training and testing accuracy after balancing the HAM10000 dataset through augmentation.

Advantages

- Uses transfer learning.
- Combines two different CNN architectures.
- Addresses class imbalance using augmentation.
- Supports multiclass skin-lesion classification.

Disadvantages

- Ensemble models computational resources. require more
- The system focuses mainly on classification.
- The model architecture can be relatively complex for deployment.

How this study addresses it:
Mahatvak Chikitsa uses multiple established CNN architectures, including VGG16, VGG19, ResNet50, and EfficientNet, for skin-lesion prediction. The system integrates the prediction with a treatment recommendation and result-display module, providing a more complete application workflow.

Feature Fusion Attention

Z. Ji et al. proposed EFAM-Net, which uses attention-based feature extraction and feature fusion for multiclass skin-lesion classification. The model was evaluated using the ISIC 2019 and HAM10000 datasets and achieved high classification accuracy on the evaluated datasets.

Advantages

- Uses attention mechanisms to focus on important image features.
- Captures features at multiple scales.
- Evaluated on multiple skin-lesion datasets.

Disadvantages

- The architecture is relatively complex.
- Attention and feature-fusion modules can increase computational requirements.
- Primarily concentrates on classification rather than end-to-end user guidance.

How this study addresses it:
This study follows a simpler and more understandable CNN-based pipeline using established architectures such as VGG16, VGG19, ResNet50, and EfficientNet. It also extends beyond classification by providing treatment recommendations and displaying the final result to the user.

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Attentional Fusion Ensemble

Ahmed et al. proposed a multi-model ensemble combining ResNet50V2, MobileNetV2, and EfficientNetV2 with an attention mechanism. The study also used preprocessing techniques for image-quality improvement, including hair-artifact removal, and evaluated the approach for different skin lesion categories.

Advantages

- Combines different CNN architectures.
- The attention mechanism helps emphasize relevant features.
- Includes preprocessing for artifacts such as hair.
- Reports precision, recall, and F1-score for different lesion types.

Disadvantages

- Combining several models increases computational requirements.
- The architecture is more difficult to implement and maintain.
- The primary focus remains skin-cancer classification.

How this study addresses it:

Mahatvak Chikitsa also uses multiple CNN architectures, but the system is designed as a complete web-based workflow: image upload, preprocessing, model prediction, classification treatment recommendation, and result display. This provides functionality beyond simply producing a classification result. Table 1. presents the quantitative performance comparison of different transfer learning architectures evaluated for skin lesion classification. The comparison is based on commonly used deep-learning approaches for skin-lesion analysis and considers their classification performance under the same preprocessing and augmentation settings.

IV. REFERENCE DESIGN

A. Overview

The proposed system is designed as a web-based framework for automated skin lesion classification using deep learning. The overall design consists of two connected stages: model development and web-based prediction. In the model development stage, images from the ISIC dataset are prepared through image cleaning, resizing, normalization, augmentation, and class balancing. The prepared dataset is then used to train and evaluate different transfer-learning models, including VGG19, VGG16, ResNet50, MobileNet, and EfficientNet. The performance of these models is compared, and the best-performing model is selected for the final prediction system. Fig. 1 presents the overall workflow of the proposed reference design

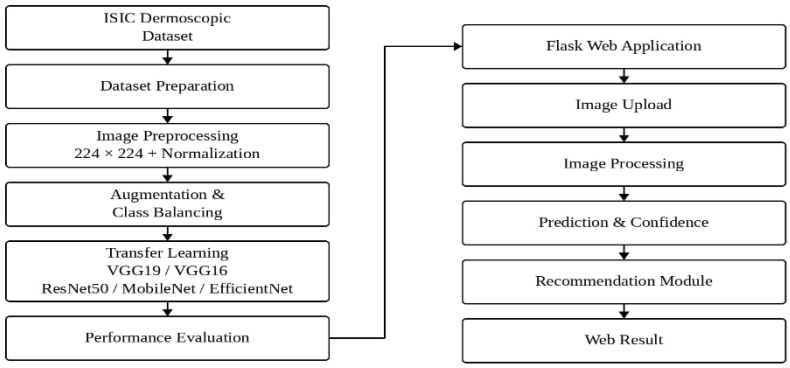


Fig. 1 Overall workflow of the proposed skin lesion classification system

B. Dataset and Image Preprocessing

The system uses dermoscopic images from the ISIC dataset for training and evaluation. Before training, the collected images undergo a preprocessing stage to make them suitable for deep learning models. The images are cleaned and resized to a common input size, followed by normalization to maintain consistent pixel values. Data augmentation is applied to increase the variation in the training images, while class balancing is used to reduce the effect of unequal numbers of samples among the lesion categories. These preprocessing operations help provide a more suitable and consistent dataset for model training.



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C. Model Development

After preprocessing, multiple transfer-learning models are developed for skin lesion classification. The selected architectures include VGG19, VGG16, ResNet50, MobileNet, and EfficientNet. Each model is adapted to perform classification of the nine target skin-lesion categories. The models are trained using the prepared dataset and evaluated using the same classification task. The use of multiple architectures allows their prediction performance to be compared before selecting the model for the final system.

D. Model Selection and Prediction

The trained models are compared based on their classification performance, and EfficientNet is selected as the final prediction model. During inference, the user uploads a dermoscopic skin image through the web application. The uploaded image is first processed using the same required preprocessing steps and is then provided to the trained EfficientNet model. The model analyses the visual features of the image and produces probability values for the nine target lesion categories. The category with the highest probability is considered the predicted lesion class.

E. Confidence Assessment

Along with the predicted lesion category, the system provides a confidence value representing the strength of the model's prediction. This value can be used to distinguish between predictions with relatively high confidence and those that may be uncertain. When the prediction is uncertain, the system can advise the user to seek further professional evaluation instead of treating the model output as a final medical diagnosis.

F. Web-Based Implementation

The trained model is integrated into a web application using the Flask framework. The application provides an interface through which users can upload dermoscopic images for analysis. The Flask backend receives the uploaded image, performs the required preprocessing, loads the trained prediction model, and generates the classification result. The frontend is implemented using HTML, CSS, and JavaScript to provide a simple interface for image submission and result display.

G. Result Presentation and Recommendation

After classification, the predicted lesion category and its confidence information are displayed on the web interface. The prediction is also connected to a recommendation module that provides general guidance associated with the predicted condition. For potentially serious categories, the system can emphasize the need for professional dermatological evaluation. The recommendation is intended only as general informational guidance and is not a replacement for medical diagnosis or treatment. Thus, the reference design connects dataset preparation, model development, model selection, image prediction, confidence assessment, and result presentation into a single workflow.

V. EXPERIMENTAL RESULTS

A. Setup

The proposed skin cancer detection system was evaluated using five transfer-learning models: VGG19, VGG16, ResNet50, MobileNet, and EfficientNet. The models were trained using dermoscopic images from the ISIC dataset. The input images were resized to 224 × 224 pixels and normalized before being provided to the models. Data augmentation techniques were applied to improve the diversity of the training images. The models were trained for 30 epochs, and their performance was evaluated using training accuracy, validation accuracy, test accuracy, precision, recall, and F1-score.

B. Comparative Performance of Models

The performance of the five models was compared using their classification results. As presented in Table I, EfficientNet achieved the highest test accuracy of 90.11%, followed by MobileNet at 85.78%, ResNet50 at 83.44%, VGG16 at 49.89%, and VGG19 at 31.44%. EfficientNet also achieved the highest precision, recall, and F1-score among the evaluated models. Based on these comparative results, EfficientNet was selected as the preferred model for the proposed skin cancer detection system.

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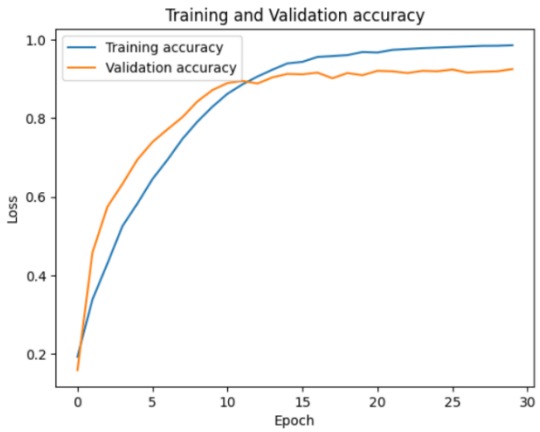
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MODELS	STEP-LOSS	ACCURACY	VALIDATION-LOSS	VALIDATION-ACCURACY
EFFICIENTNET	0.3769	0.9850	0.6894	0.9244
MOBILENET	0.3107	0.9925	0.8570	0.8889
RESNET50	0.1866	0.9899	0.9738	0.8422
VGG16	1.0806	0.6136	1.5830	0.4944
VGG19	1.0939	0.5918	3.3810	0.2756

C. Training and Validation Performance

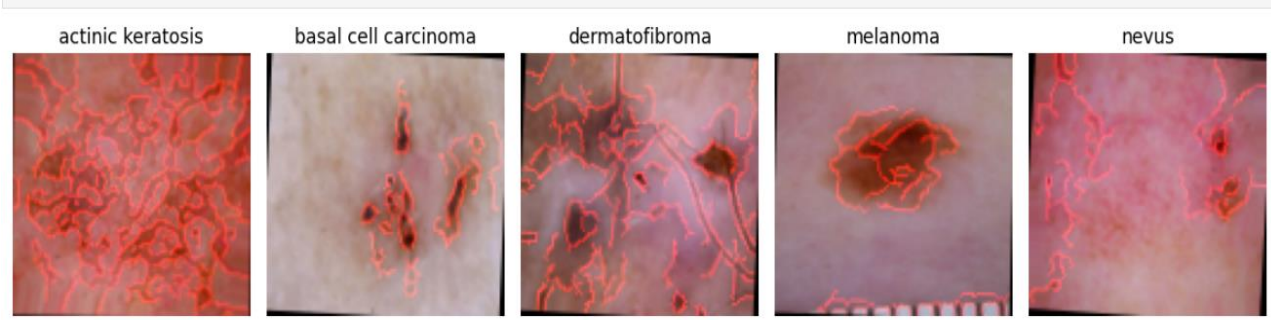
The training and validation results were examined to understand the learning behaviour of EfficientNet. The model achieved a training accuracy of 98.50% and a validation accuracy of 92.44%. MobileNet recorded a training accuracy of 99.25% and a validation accuracy of 88.89%. Although MobileNet achieved higher training accuracy, EfficientNet performed better on the validation and test datasets. This comparison indicates that training accuracy alone is not sufficient for selecting the best-performing model.





D. Class-wise Performance Analysis

The class-wise evaluation of EfficientNet was used to examine its performance across the nine skin lesion categories. The precision, recall, and F1-score values differed between classes. Strong results were obtained for several categories, including basal cell carcinoma, dermatofibroma, pigmented benign keratosis, squamous cell carcinoma, and vascular lesions. However, the recall values for melanoma and nevus were lower than those for some other classes. This analysis highlights the importance of evaluating individual lesion categories in addition to overall model accuracy.



E. Grad-CAM Visualization

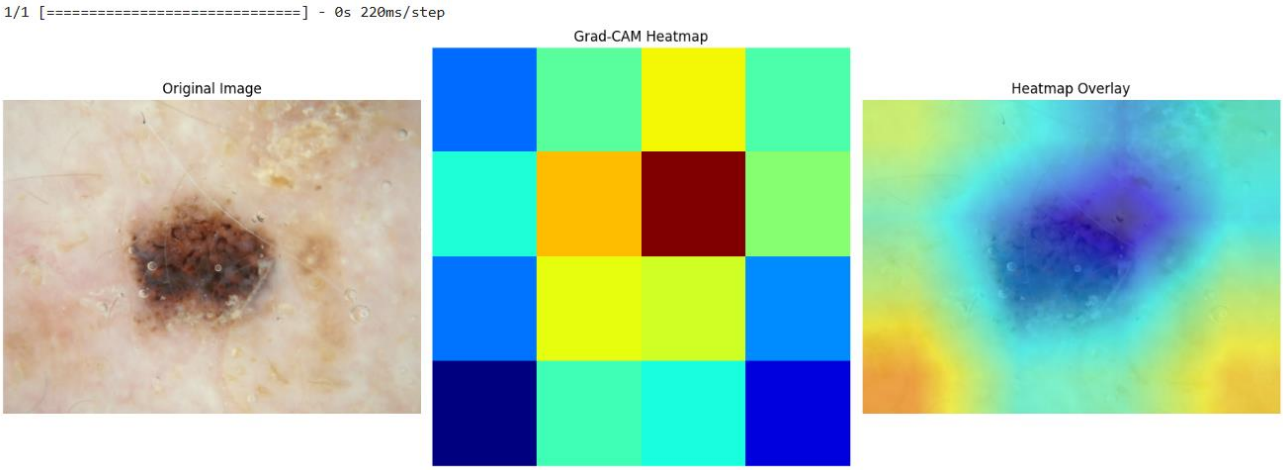
Grad-CAM was used to visualize the image regions that contributed to the model's prediction. The visualization consists of the original dermoscopic image, a heatmap, and an overlay combining the heatmap with the original image. These visualizations provide insight into the regions influencing the model's output and help make its predictions easier to interpret. However, they do not independently establish the medical correctness of a prediction.

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F. Web Application Results

The trained classification model was integrated into a web application to demonstrate the practical use of the proposed system. The application allows users to upload a dermoscopic image and displays the predicted skin lesion category with its confidence score. This interface provides an accessible way to view the model's output. The prediction and any accompanying informational guidance are intended for preliminary information and should not replace assessment by a qualified healthcare professional.

VI. DISCUSSION

A. Comparative Performance of Deep Learning Models

The experimental evaluation shows that the five deep learning models achieved different levels of performance in skin lesion classification. VGG19 obtained a test accuracy of 31.44%, whereas VGG16 achieved 49.89%. ResNet50 performed considerably better, reaching 83.44%, while MobileNet achieved 85.78%. Among the evaluated models, EfficientNet recorded the highest test accuracy of 90.11%. These results show that the choice of model has a considerable effect on the classification performance of the proposed system.

B. Analysis of EfficientNet Performance

EfficientNet achieved a macro-precision of 0.9085, macro-recall of 0.9065, and macro F1-score of 0.9057. These values indicate that the model achieved strong overall performance across the nine skin lesion categories. Its comparatively high precision and recall suggest that it performed well in identifying the target categories while balancing correct predictions and the identification of relevant cases. However, performance should be examined for each class because an overall accuracy value does not fully describe the model's behaviour across all lesion types.

C. Comparison with Other Models

MobileNet and ResNet50 also showed competitive classification results, with test accuracies of 85.78% and 83.44%, respectively. Although their performance was lower than that of EfficientNet, both models performed better than VGG16 and VGG19 in the reported experiments. VGG19 achieved the lowest test accuracy among the five models, followed by VGG16. This comparison helped identify EfficientNet as the preferred model for the final implementation based on the evaluation results obtained in this project.

D. Class-Wise Classification Observations

The class-wise evaluation of EfficientNet shows that performance was not identical across all nine lesion categories. The model achieved strong F1-scores for dermatofibroma, pigmented benign keratosis, and vascular lesions. Comparatively lower F1-scores were observed for nevus and actinic keratosis. Such differences indicate that certain categories may be more difficult for the model to distinguish. Examining class-wise precision, recall, and F1-score provides a clearer understanding of these differences than relying on overall accuracy alone.

E. Integration into the Web Application

Based on the comparative evaluation, EfficientNet was selected for integration into the MAHATVAK CHIKITSA web application. The application uses a Flask backend and a frontend developed with HTML, CSS, and JavaScript. Users can upload a skin lesion image, which is processed before being passed to the trained model. The application then displays



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the predicted lesion category and its confidence score. This implementation provides an accessible interface for demonstrating the classification capabilities of the selected model.

F. Practical Significance

The proposed system demonstrates how deep learning can be applied to the preliminary classification of skin lesion images. Displaying a predicted category and confidence score can help users understand the model's output. Nevertheless, the predicted category should not be interpreted as a confirmed diagnosis, and the confidence score does not establish clinical certainty. The application is intended as a preliminary decision-support tool and should not replace assessment by a qualified dermatologist.

VII. FUTURE DIRECTIONS

Validating the system on larger, more diverse datasets and external clinical cohorts will be crucial to ensure robust real-world reliability across varied demographics. Integrating Explainable AI (XAI) techniques like Grad-CAM will provide visual interpretability, helping clinicians trust and verify the model's decision-making process. Finally, optimizing the pipeline into a lightweight mobile application will expand its reach, delivering instant, point-of-care dermatological screening to underserved communities.

VIII. CONCLUSION

MAHATVAK CHIKITSA was developed as an end-to-end deep learning framework for classifying skin lesions from dermoscopic imagery across nine distinct categories. Among the five transfer learning architectures evaluated—VGG16, VGG19, ResNet50, MobileNet, and EfficientNet—EfficientNet demonstrated superior overall performance, achieving a peak test accuracy of 90.11% and a macro F1-score of 0.9057. The model was seamlessly deployed into an interactive Flask web application that translates raw predictions into actionable outputs, delivering category predictions, confidence scores, and tailored preliminary treatment recommendations. Ultimately, this system highlights the viable role of AI as an accessible, supportive screening tool for dermatological decision support, while underscoring that final diagnoses must always remain in the hands of qualified healthcare professionals.

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