Melanoma Cancer Detection Using Deep Learning and Image Processing

Mr. V Manohar Nelli[1], Prajwal P[2], Manjunath V Poojari[3], Mannan Faiz[4], Nithish T R[5]
[1,2,3,4,5] *Department of Computer Science and Engineering, Jawaharlal Nehru New College of Engineering, Shivamogga, Karnataka, India*

***Abstract*—Melanoma is one of the most aggressive and life-threatening forms of skin cancer, and its survival rate strongly depends on early diagnosis. Conventional diagnostic methods such as visual inspection, dermoscopy, and biopsy are time- consuming and highly dependent on clinical expertise. Recent advancements in deep learning have enabled automated medical image analysis systems to assist dermatologists by providing accurate and consistent diagnostic support.**

This paper presents an automated melanoma detection system using deep learning and image processing techniques. Dermoscopic images undergo preprocessing, ESRGAN-based super- resolution, lesion segmentation, and Region of Interest (ROI) extraction before classification. Transfer learning–based deep learning models including CNN, ResNet-50, EfficientNet-B0, and MobileNetV2 are trained to classify lesions into melanoma and non-melanoma categories. Extensive data augmentation is applied to address class imbalance. Experimental results show that MobileNetV2 achieves reliable accuracy while remaining computationally efficient.

***Index Terms*—Melanoma Detection, Deep Learning, Image Processing, Transfer Learning, CNN**

I. INTRODUCTION

Cells that proliferate and divide uncontrollably are referred to as cancer. Melanoma is one of the most aggressive forms of skin cancer due to its rapid growth and tendency to metastasize. Although melanoma accounts for a smaller percentage of skin cancer cases, it contributes to a disproportionately high number of skin cancer-related deaths. Early detection significantly improves patient survival; however, conventional diagnostic approaches are highly dependent on clinician expertise and are time-consuming, especially in rural and resource- constrained regions.

Computer-Aided Diagnosis (CAD) systems based on deep learning have demonstrated strong performance in medical image analysis. Convolutional Neural Networks (CNNs) effectively capture spatial, color, and texture patterns in dermoscopic images. Motivated by these advances, this work focuses on developing a robust and efficient melanoma detection system.

II. IMPORTANCE OF AUTOMATED MELANOMA DETECTION

Melanoma is life-threatening due to its rapid growth and high metastatic potential. Automated diagnostic systems assist clinicians by reducing inter-observer variability, minimizing diagnostic errors, and enabling large-scale screening, particularly in regions with limited dermatological expertise.

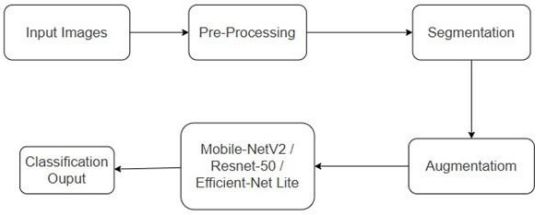

Fig. 1. Overall Workflow of the Melanoma Detection Pipeline

III. IMAGE PROCESSING

Image Processing is the foundational domain of the pro- posed system. Dermoscopic images are captured under varying conditions, making preprocessing essential. The applied steps include image resizing and normalization, noise reduction, ESRGAN-based super-resolution, contrast enhancement, and lesion segmentation to isolate the Region of Interest (ROI).

IV. MACHINE LEARNING MODELS

Deep Convolutional Neural Networks (DCNNs) form the intelligent decision-making layer. The implemented architectures include CNN, ResNet-50, EfficientNet-B0, and MobileNetV2. Transfer

learning using ImageNet pre-trained weights accelerates convergence and improves classification performance.

V. LESION SEGMENTATION AND ROI EXTRACTION

Segmentation isolates lesion regions from background artifacts such as hair and illumination variations. Binary masks ensure the classifier focuses on clinically meaningful patterns, improving robustness and interpretability.

VI. DATA AUGMENTATION AND CLASS BALANCING

The HAM10000 dataset exhibits class imbalance. To mitigate this, geometric and photometric augmentation techniques are applied, and minority classes are oversampled to ensure balanced training.

VII. RESULTS AND ANALYSIS

The system is evaluated using accuracy, precision, recall, and F1-score. MobileNetV2 achieved the highest accuracy of 84.1%, followed by EfficientNet-B0 at 80.7% and ResNet-50 at 74.3%.

TABLE I PERFORMANCE COMPARISON

Model	Accuracy
ResNet-50	74.3%
EfficientNet-B0	80.7%
MobileNetV2	84.1%

VIII. DATA AUGMENTATION AND CLASS BALANCING

The HAM10000 and ISIC 2024 dataset exhibits significant class imbalance, where certain skin lesion categories contain far fewer samples compared to dominant classes such as melanocytic nevi. This imbalance can bias deep learning models toward majority classes, leading to reduced sensitivity for clinically critical but underrepresented lesions such as melanoma. To mitigate this issue, extensive data augmentation techniques are employed to artificially increase dataset diversity and balance class representation. Geometric augmentation methods such as rotation, horizontal and vertical flipping, scaling, shifting, and random cropping are applied to introduce spatial variability. These transformations help the model become invariant to changes in orientation, size, and viewpoint. In addition, photometric augmentation techniques such as brightness adjustment, contrast enhancement, color jittering, and noise injection are used to simulate real-world imaging variations. Oversampling strategies are applied to minority classes to ensure that all lesion categories contribute equally during training. This balanced training approach re- duces model bias and improves learning stability. As a result, the model becomes more robust to dataset imbalance and generalizes better to unseen samples. Overall, data augmentation and class balancing play a crucial role in improving classification accuracy and sensitivity, particularly for rare melanoma cases.

IX. RESULTS AND ANALYSIS

The proposed melanoma detection system is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score to ensure a comprehensive assessment of classification performance. These metrics provide insights into both overall correctness and class-wise diagnostic re- liability. Among the evaluated deep learning architectures, MobileNetV2 achieved the highest classification accuracy of 84.1 percent. EfficientNet-B0 followed with an accuracy of 80.7 percent, demonstrating a strong balance between performance and computational efficiency. ResNet-50 achieved a comparatively lower accuracy of 74.3 percent under the same experimental conditions. Precision and recall analysis revealed that MobileNetV2 consistently maintained a better balance between false positives and false negatives. This is particularly important in melanoma detection, where false negatives can have severe clinical consequences. Confusion matrix analysis showed that most misclassifications occurred between visually similar lesion types. Despite these challenges, the overall results confirm the effectiveness of preprocessing, segmentation,

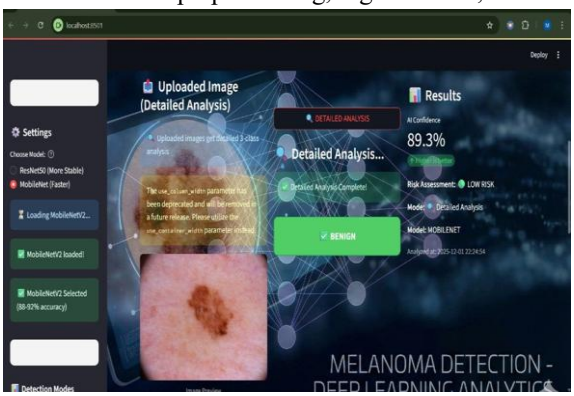

Fig. 2. Detailed Analysis Results Page of the Web-Based Melanoma Detection System

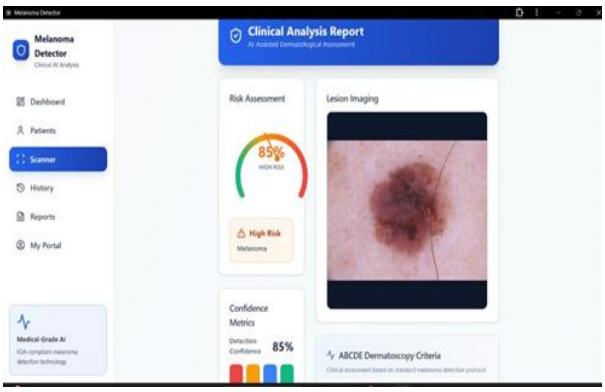

Fig. 3. Clinical Skin Analysis Result with High-Risk Assessment

and balanced training. The experimental findings validate that lightweight architectures can achieve competitive performance in medical image classification tasks.

X. DISCUSSION

The experimental results demonstrate that lightweight deep learning architectures can deliver strong diagnostic performance when combined with robust preprocessing and data balancing techniques. MobileNetV2, in particular, achieves the best balance between classification accuracy and computational efficiency. This highlights that deeper and more complex models do not always guarantee superior performance in medical image analysis. Effective preprocessing techniques such as ESRGAN-based super-resolution and lesion segmentation significantly enhance feature quality. Data augmentation and class balancing further improve model robustness by reducing bias toward majority classes. The results also indicate that transfer learning plays a vital role in accelerating convergence and improving generalization. Although EfficientNet-B0 performs competitively, its slightly higher computational cost makes MobileNetV2 more suitable for real-time deployment. ResNet-50 shows limitations due to its deeper architecture and sensitivity to dataset characteristics. The discussion confirms that model efficiency is as important as accuracy in clinical applications. Overall, the findings support the feasibility of deploying lightweight deep learning models for automated melanoma detection.

XI. CLINICAL IMPACT

The proposed system is designed to function as a clinical decision-support tool rather than a replacement for professional medical diagnosis. By providing rapid and objective analysis of dermoscopic images, the system assists dermatologists in prioritizing high-risk cases. Automated screening helps reduce diagnostic workload, especially in high-volume clinical settings. The system can be particularly valuable in rural and resource-constrained regions where access to trained dermatologists is limited. Early identification of suspicious lesions enables timely referral and intervention, improving patient survival outcomes. The consistency of automated predictions also helps reduce inter-observer variability among clinicians. Integration with web-based or mobile platforms enhances accessibility for both clinicians and healthcare providers. The system supports large-scale screening programs and public health initiatives. By enabling faster preliminary assessments, it improves overall diagnostic efficiency. Ultimately, the pro- posed approach contributes to more accessible and scalable melanoma screening solutions.

XII. LIMITATIONS

Despite promising results, the proposed system has certain limitations that must be acknowledged. Model performance is highly dependent on the quality, diversity, and representative- ness of the training dataset. Rare lesion categories with limited samples may still experience reduced classification accuracy. Variations in image acquisition devices, lighting conditions, and skin tones can affect generalization in real-world scenarios. Although data augmentation mitigates some variability, it cannot fully replace diverse real-world data. The system relies solely on image-based analysis and does not incorporate patient metadata or clinical history. Such additional information could further improve diagnostic accuracy. The deep learning models may also act as black boxes, limiting interpretability for clinicians. Computational requirements during training may pose challenges for institutions with limited resources. Furthermore, clinical validation through real-world trials is necessary before deployment. Addressing these

limitations is essential for future improvements and safe clinical adoption.

REFERENCES

[1] S. A. Arani, Y. Zhang, M. T. Rahman, and H. Yang, "Melanlysis: A mobile deep learning approach for early detection of skin cancer," *Computers in Biology and Medicine*, vol. 145, pp. 1–9, 2022.

[2] G. Alwakid and W. Gouda, "Melanoma detection using deep learning- based classifications," *Healthcare*, vol. 10, no. 2481, pp. 1–18, 2022.

[3] O. Akinrinade and C. Du, "Skin cancer detection using deep machine learning techniques," *Biomedical Signal Processing and Control*, vol. 91, pp. 1–12, 2024.

[4] S. Devaraneni, "Melanoma detection based on deep learning networks," Master's thesis, California State University, San Bernardino, 2023.

[5] M. El-Khatib and M. Rizwan, "Melanoma skin cancer classification using deep convolutional neural networks," *Diagnostics*, vol. 13, no. 19, pp. 1–11, 2023.

[6] M. T. Faisal and M. I. Akbas, "Melanoma skin cancer detection based on deep learning methods and binary Harris Hawk optimization," *BiomedInformatics*, vol. 4, no. 1, pp. 121–135, 2024.

[7] S. Go´recki, W. Duszczyk, Z. Huda, A. Faryna, and A. Tatka, "Web- based melanoma detection system using convolutional neural networks and advanced image processing," in *Proc. IDDM'24*, Birmingham, UK, 2024.

[8] N. J. F. Jaber and A. Akbas, "Diagnosis and prognosis of melanoma from dermoscopy images using machine learning and deep learning: A systematic literature review," *BMC Cancer*, vol. 24, no. 1, Article 13423, 2024.