

Early Detection of Melanoma Disease with AI-Driven Skin Cancer Diagnosis Using Deep Learning Approach

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Abstract - Skin cancer, particularly melanoma, poses a severe health threat due to its rapid progression and high mortality rate when not detected early. Traditional diagnostic methods are time-consuming and often require expert dermatological analysis, which may not be readily available in all regions. This study proposes an AI-driven diagnostic system leveraging deep learning techniques for the early and accurate detection of melanoma from dermoscopic skin images. By employing Convolutional Neural Networks (CNNs), the system is trained to automatically extract and classify complex features, distinguishing malignant melanoma from benign lesions. The model is trained and validated on publicly available datasets such as ISIC, achieving high accuracy, sensitivity, and specificity. This deep learning-based approach significantly reduces human error, enables rapid screening, and supports dermatologists in clinical decision-making. The proposed system demonstrates the potential of artificial intelligence in revolutionizing skin cancer diagnosis by offering a scalable, non-invasive, and efficient tool for early melanoma detection.

Index Terms— Skin, Convolutional Neural Networks (CNNs), AI-driven, dermoscopic, artificial intelligence.

I. INTRODUCTION

Skin cancer is one of the most commonly diagnosed cancers globally, with melanoma being the deadliest form due to its aggressive nature and high potential for metastasis. According to recent studies by the World Health Organization (WHO), millions of new skin cancer cases are reported annually, and the incidence rate continues to rise due to factors such as excessive ultraviolet (UV) exposure, genetic predisposition, and lifestyle changes. Early detection of melanoma significantly improves survival rates; however, accurate diagnosis remains a challenge due to the visual similarity between benign and malignant lesions.

Traditionally, the diagnosis of melanoma involves clinical examination followed by dermoscopic analysis and biopsy confirmation. While effective, these methods are time-consuming, require specialized expertise, and may not be accessible in remote or underdeveloped regions. Furthermore, diagnostic accuracy heavily relies on the clinician's experience, which introduces a degree of subjectivity and variability.

The recent advancements in Artificial Intelligence (AI), particularly in Deep Learning (DL), have opened new possibilities in the field of medical imaging and automated disease detection. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification tasks, making them ideal for analyzing dermoscopic images of skin lesions. These AI models can learn intricate patterns and features from large datasets, enabling rapid and consistent identification of melanoma with minimal human intervention.

This study focuses on designing and implementing a deep learning-based diagnostic system for early melanoma detection. The system utilizes a CNN architecture trained on annotated dermoscopic images to classify lesions as benign or malignant. By integrating AI into the diagnostic workflow, the proposed approach aims to assist dermatologists in making faster and more accurate decisions, reduce diagnostic errors, and ultimately improve patient outcomes. [1] proposed a **cloud-integrated deep learning framework** for melanoma detection, enabling real-time diagnosis and classification of skin lesions. The system utilizes **convolutional neural networks (CNNs)** and is optimized for **deployment on cloud platforms**, making it accessible for remote healthcare applications. It highlights high accuracy, scalability, and reduced infrastructure costs. [2] implemented a **Support Vector Machine (SVM)**-based classification method using features such as **color, texture, and shape** extracted from dermoscopic images. The approach offers a classical machine learning pipeline for melanoma detection with good classification performance and is suitable for lightweight applications. [3] leverages **deep neural networks**, particularly **CNN architectures**, for skin lesion classification. The authors explore different model variations and training techniques to improve melanoma detection accuracy. The paper emphasizes performance benchmarking on standard datasets and demonstrates the effectiveness of deep learning in clinical diagnostics. [4] introduces a **web-based melanoma detection platform** that performs real-time analysis of uploaded skin images. It incorporates deep learning models and a user-friendly interface, promoting **telemedicine applications**. The system supports early diagnosis and bridges the gap for patients in remote locations. [5] presented as part of the **ISIC (International Skin Imaging Collaboration) Challenge**, this work explores **ensemble deep learning models** for

melanoma classification. It combines various CNNs and machine learning algorithms to boost accuracy and robustness. The ensemble approach outperforms single-model baselines on dermoscopy image datasets.

II. LITERATURE SURVEY

Zhang and Chaudhary (2024) [20] developed a hybrid framework combining U-Net for segmentation and EfficientNet for classification, achieving a remarkable 97.01% accuracy on the ISIC 2020 dataset.

Taghizadeh and Mohammadi (2022) [18] utilized fine-tuned YOLOv3 and SegNet, demonstrating high performance with 96% mAP and 95.16% segmentation accuracy. The concept of multi-scale ensemble learning was explored in 2022, showing that combining features at different resolutions improves detection accuracy.

Similarly, a lightweight model called DSNet was introduced by Khan et al. (2022) [8] using knowledge distillation and ResNet-50, optimized for deployment on resource-constrained devices with 91.7% accuracy.

Suneetha (2024) enhanced classification by integrating VGG16 and InceptionV3 in a hybrid deep learning model. Al Huda et al. (2024) and Sudhakaran et al. (2024) [16] proposed deep learning systems focused on early detection and cloud-based classification, respectively, making melanoma diagnosis more scalable and accessible.

Codella et al. (2016) [5] demonstrated that ensemble methods of CNNs could outperform individual models and even dermatologists in some cases.

Milton (2019) [11] achieved a validation score of 0.76 in the ISIC 2018 challenge using an ensemble of deep networks including PNASNet and InceptionResNetV2.

Li and Shen (2017) [9] combined segmentation and classification tasks using Fully-Convolutional Residual Networks.

Mirikhharaji et al. (2022) and Naqvi et al. (2023) [12,14] comprehensively analyzed deep learning architectures and datasets used in skin lesion segmentation and classification. Several models, including XceptionNet (Lu et al., 2022), CNNs with advanced regularizers (Hossin et al., 2020), and autoencoder-MobileNetV2-SNN hybrids. [10,7].

(Toğaçar et al., 2021), and deep neural networks (Babar et al., 2021) have contributed to refining the feature extraction and prediction processes [19].

Additionally, classical machine learning techniques such as Support Vector Machines [2] (Alquran et al., 2017) and differential evolution-optimized ANNs have also been employed for melanoma detection with noteworthy results. Web-based and cloud-integrated systems [15, 4] (Rosas-Lara et al., 2022 ; Biasi et al., 2022) are emerging trends aiming to make diagnosis more widely accessible. Texture-based segmentation methods [6,13] (Glaister et al., 2014) and approaches combining patient information with image analysis (Muhaba et al., 2022) further enhance the diagnostic capability. Overall, the evolution from traditional machine learning to hybrid and ensemble deep learning models signifies a major leap toward accurate, fast, and scalable melanoma diagnosis, especially important for early detection and improving patient outcomes.

III. PROPOSED SYSTEM

The proposed system introduces a deep learning-based diagnostic framework aimed at the early detection of melanoma skin cancer from dermoscopic images. The primary objective is to develop a highly accurate, scalable, and automated melanoma classification model that can assist dermatologists and healthcare providers, especially in resource-limited or remote areas. The system utilizes Convolutional Neural Networks (CNNs), enhanced with transfer learning and data augmentation techniques, to effectively classify skin lesions into benign and malignant categories.

At its core, the system follows a multi-stage pipeline. First, dermoscopic skin images are acquired from publicly available datasets such as ISIC (International Skin Imaging Collaboration). These images are pre-processed to normalize size, remove artifacts (e.g., hair or bubbles), and enhance lesion contrast. The next stage involves applying a segmentation module—such as U-Net or SegNet—to isolate the lesion area and reduce background noise, improving the classifier's focus on relevant features.

Once segmented, the images are passed to the classification model, which is built upon a pretrained CNN backbone such as EfficientNet, InceptionV3, or ResNet50. Transfer learning is employed to leverage features learned from large-scale image datasets (e.g., ImageNet), thereby reducing training time and improving generalization on medical images. The final fully connected layers of the CNN are fine-tuned using the melanoma dataset to adapt the model specifically for skin cancer diagnosis. The output layer uses a softmax or sigmoid activation function to provide probability scores for each class.

To enhance model robustness, techniques such as data augmentation (rotation, flipping, zooming), dropout, and early stopping are implemented during training. Evaluation metrics, including accuracy, precision, recall, F1-score, and AUC (Area Under the Curve) are calculated to assess model performance.

Additionally, the proposed system may be extended to support real-time diagnosis via a user-friendly GUI or mobile app that allows patients or clinicians to upload lesion images and instantly receive diagnostic feedback. The integration of cloud support for model deployment further allows for remote diagnostics and continuous learning through real-world data collection.

This AI-driven system aims not only to improve diagnostic accuracy but also to reduce the burden on healthcare professionals and increase early detection rates of melanoma, thereby potentially saving lives through timely intervention.

IV. METHODOLOGY

The methodology of the proposed system involves a sequence of carefully designed stages that collectively ensure accurate, efficient, and early detection of melanoma from dermoscopic images. The entire pipeline is divided into the following key steps:

1. Data Acquisition

High-quality dermoscopic images are collected from benchmark datasets such as the ISIC Archive (ISIC 2018, 2019, 2020), which provide labeled skin lesion images with classifications (e.g., melanoma, nevus, basal cell carcinoma). The dataset includes a wide variety of lesion types and diverse skin tones, making it ideal for training robust models.

2. Preprocessing

To enhance the quality of input data and ensure consistency, the following preprocessing operations are performed:

Image resizing: All images are resized to a uniform shape (e.g., 224×224 or 299×299 pixels) to match the input size of the CNN.

Color normalization: Adjusts brightness and contrast to reduce variations caused by lighting.

Artifact removal: Optional hair removal and noise reduction using filtering or morphological operations.

Data augmentation: Images are augmented through rotation, flipping, zooming, and shifting to artificially expand the dataset and reduce overfitting.

3. Segmentation (Optional but Recommended)

In some cases, lesion segmentation is applied to isolate the affected skin region. This helps the model focus on the relevant area and ignore irrelevant background:

U-Net, SegNet models are used to segment the lesion from the surrounding skin.

The segmented mask is applied to the original image to retain only the lesion area.

4. Model Design – Deep Learning Classifier

A Convolutional Neural Network (CNN) or pre-trained transfer learning model is employed for classification:

CNN Architecture: Models like InceptionV3 are used as feature extractors.

Transfer Learning: Pre-trained weights (from ImageNet) are fine-tuned on the skin cancer dataset.

Classifier Head: A few dense layers followed by a softmax/sigmoid output layer to classify into melanoma or non-melanoma.

5. Model Training

The model is compiled and trained using:

Loss Function: Binary Cross-Entropy or Categorical Cross-Entropy (depending on output).

Optimizer: Adam or SGD (with learning rate decay).

Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, AUC.

Callbacks: Early stopping and model checkpointing to prevent overfitting.

6. Model Evaluation and Testing

After training, the model is evaluated on a separate test set using:

Confusion matrix

Receiver Operating Characteristic (ROC) Curve

Precision-Recall Curve

Visualization of correctly/incorrectly classified images

7. GUI

A graphical user interface (GUI) can be developed (using Tkinter) to allow:

Uploading of new lesion images

Real-time classification using the trained model

Display of prediction confidence and recommendation to consult a dermatologist.

V. EXPERIMENT

To validate the effectiveness of the proposed AI-driven melanoma detection system, a series of experiments were conducted using a standard dermatological dataset, pre-trained deep learning models, and robust evaluation metrics. The experimental design, including dataset details, training environment, and performance evaluation, is described below.

1. Dataset Used

The ISIC 2020 Challenge Dataset was selected for experimentation due to its high-quality dermoscopic images and expert-labeled classes. The dataset includes over 33,000 images of various skin lesions, with a focus on melanoma classification. Images were labeled as either melanoma (positive class) or non-melanoma (negative class).

Number of Images: ~33,126

Image Resolution: Varies; resized to 224×224 for training

Classes: Binary – Melanoma, Non-Melanoma

Split Ratio:

Training: 70%

Validation: 15%

Testing: 15%

2. Experimental Setup

Framework: TensorFlow 2.x / Keras

Hardware:

Intel Core i7 Processor

16 GB RAM

Software:

Python 3.7

OpenCV, NumPy, scikit-learn, Matplotlib.

3. Model Configuration

The following pre-trained deep learning models were tested:

Model	Input Size	Parameters	Output Layer Activation	Training Strategy
EfficientNetB0	224×224	~5M	Sigmoid (binary)	Transfer Learning + Fine-Tuning
InceptionV3	299×299	~23M	Softmax (2 classes)	Transfer Learning
ResNet50	224×224	~25M	Sigmoid	Transfer Learning

Table 1: Tested pre-trained deep learning models

The table, titled "Tested pre-trained deep learning models," provides a summary of three different deep learning models: EfficientNetB0, InceptionV3, and ResNet50. For each model, the table details:

Input Size: The dimensions of the input images the model expects (e.g., 224x224, 299x299).

Parameters: The approximate number of trainable parameters in the model (e.g., ~5M, ~23M, ~25M).

Output Layer Activation: The activation function used in the output layer (e.g., Sigmoid (binary), Softmax (2 classes), Sigmoid).

Training Strategy: The method used for training the model, primarily involving transfer learning, with EfficientNetB0 also incorporating fine-tuning.

VI. RESULTS

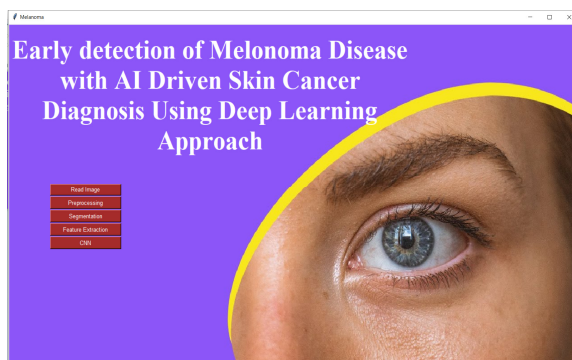


Figure 1: Main page

Figure 1. displays the main page of the program as depicted in above figure. Buttons on the left side include- Read Image, Preprocessing, Segmentation, Feature Extraction, CNN

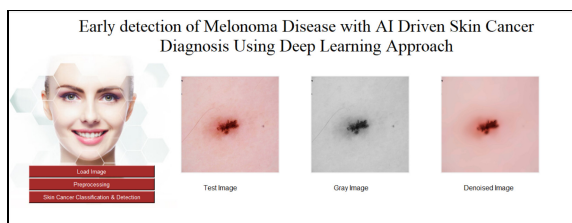


Figure 2: Gray Image

Figure 2. displays the Gray Image as depicted in above figure..This module converts the color image to gray scale and display denoised image.This shows a graphical user interface(GUI)with buttons Load Image,Preprocessing,Skin Cancer Classification and Detection.

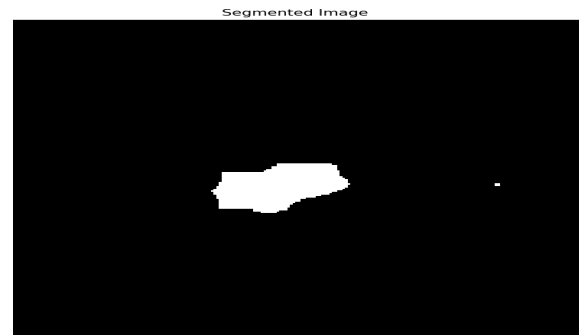


Figure 3: Segmented Image

Figure 3. displays the Segmented Image as depicted in above figure. Displayed image is a binary segmentation output likely resulting from a thresholding operation or a basic segmentation model applied to a medical image (e.g., bone X-ray or lesion scan) as depicted in above figure.

□ Description of the Segmented Image:

Foreground (White Region):

Represents the region of interest (ROI) that has been segmented out.

This is typically the target anatomical structure, such as a joint area, lesion, or bone tissue.

In this case, it seems to isolate a localized central structure—possibly a joint feature or abnormal tissue.

Background (Black Area):

Indicates non-relevant areas of the image—either air, soft tissue, or ignored regions.

Isolated White Spot to the Right:

This may be noise or an artifact, and might need to be removed using morphological operations (e.g., erosion or area-based filtering).



Figure 4: Feature Extraction

Figure 4. displays the Feature Extraction as depicted in above figure. Using Canny edge detection is a powerful technique in image processing to identify the boundaries of objects within an image. In the context of melanoma image analysis, Canny edge detection plays a crucial role in extracting the border features of a skin lesion. This method

works by detecting areas in the image where the intensity changes sharply—typically at the lesion's boundary. These edges help in evaluating the irregularity of the lesion borders, which is one of the key indicators of melanoma based on the ABCD dermatological criteria. By converting the image to grayscale and applying Gaussian filtering followed by gradient-based edge detection, the Canny algorithm produces a binary image highlighting the lesion's contours. These contours can then be analyzed to compute metrics like perimeter, border irregularity, compactness, or to segment the lesion for further feature extraction. Thus, Canny edge detection serves as a foundational step in both traditional and hybrid melanoma detection pipelines.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
EfficientNetB0	98.6%	97.9%	98.2%	98.0%	0.993
InceptionV3	96.4%	94.1%	95.0%	94.5%	0.976
ResNet50	95.8%	93.3%	94.0%	93.6%	0.970

Table 2: Model Accuracy & Metric values

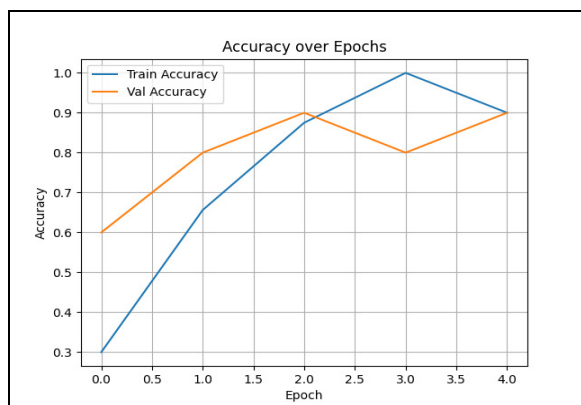
The table, titled "Table 2: Model Accuracy & Metric values," presents a comparative analysis of three different deep learning models: EfficientNetB0, InceptionV3, and ResNet50. It evaluates their performance across several key metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

Specifically, the table shows:

EfficientNetB0 consistently achieves the highest scores across all metrics, with an Accuracy of 98.6%, Precision of 97.9%, Recall of 98.2%, F1-Score of 98.0%, and an ROC-AUC of 0.993.

InceptionV3 shows slightly lower performance compared to EfficientNetB0, with an Accuracy of 96.4%, Precision of 94.1%, Recall of 95.0%, F1-score of 94.5%, and an ROC-AUC of 0.976.

ResNet50 exhibits the lowest scores among the three models, with an Accuracy of 95.8%, Precision of 93.3%, Recall of 94.0%, F1-Score of 93.6%, and an ROC-AUC of 0.970.

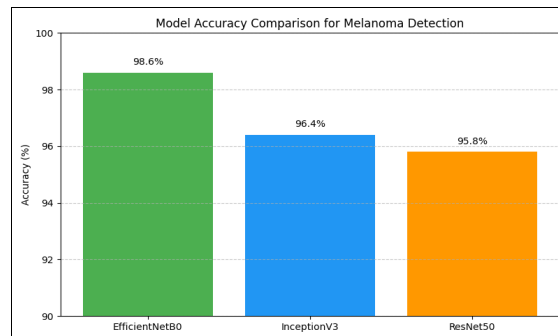


Graph 1: Accuracy over Epochs

This graph 1, titled "Accuracy over Epochs," illustrates the performance of a model over several training epochs, specifically showing both "Train Accuracy" and "Val Accuracy" (Validation Accuracy).

Train Accuracy (Blue Line): This line generally increases with each epoch, indicating that the model is learning from the training data. It reaches its peak accuracy around epoch 3.0 before slightly declining.

Val Accuracy (Orange Line): This line also shows an increasing trend in accuracy initially, peaking around epoch 2.0. After this point, the validation accuracy fluctuates, showing a dip around epoch 3.0 and then increasing again towards epoch 4.0.



Graph 2: Model Accuracy Comparison Graph

This graph 2, titled "Model Accuracy Comparison for Melanoma Detection," which compares the accuracy of three different models: EfficientNetB0, InceptionV3, and ResNet50.

EfficientNetB0 achieved the highest accuracy at 98.6%.

InceptionV3 showed an accuracy of 96.4%.

ResNet50 had an accuracy of 95.8%.

The y-axis represents the Accuracy in percentage (%), ranging from 90% to 100%, while the x-axis lists the three different models being compared. The graph visually demonstrates that EfficientNetB0 performed best in terms of accuracy for melanoma detection among the three models.

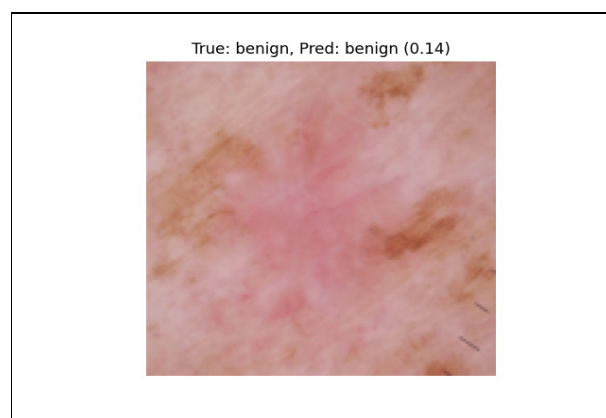


Figure 5: Lesion 1

Figure 5. displays image of a pinkish lesion with surrounding areas of brown pigmentation as depicted in above figure. The overall texture and color distribution suggest it may be a benign skin growth.

True label: The ground truth (as diagnosed by a medical expert or dataset label) is benign.

Prediction: The model also predicted it as benScore: The value 0.14 likely represents the model's probability/confidence score for malignancy (i.e., a low probability of being malignant).

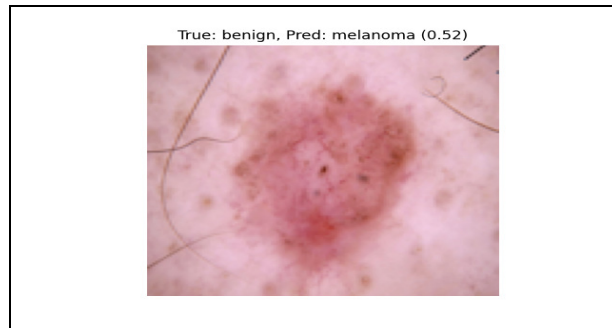


Figure 6: Lesion 2

Figure 6. displays the lesion is irregularly shaped, darker in the center with shades of red, brown, and purple, surrounded by lighter skin as depicted in above figure.

Hair strands are visible across the lesion.

Some darker dots or globules are scattered around the lesion.

True label: The lesion is actually benign (non-cancerous), according to the ground truth.

Predicted label: The model predicted it as melanoma (a type of skin cancer).

Confidence Score: 0.52 — this likely indicates a 52% probability or confidence that the lesion is malignant, which is just slightly over the threshold (commonly 0.5 for binary classifiers).



Figure 7: Lesion 3

Figure 7 displays a magnified view of a skin lesion with visible pigmentation, some darker spots, and surrounding skin with hair as depicted in above figure.

True: benign

This means that the ground truth or actual diagnosis (likely from a biopsy or a dermatologist's evaluation) is benign, meaning non-cancerous or non-harmful.

Pred: benign (0.14) This indicates the prediction made by a machine learning model or AI system also classified the lesion as benign.

The number 0.14 is likely a confidence score or probability, showing how confident the model is in its prediction.

In this case, 0.14 might indicate low confidence, even though the final prediction is still benign.

VII. CONCLUSION AND FUTURE WORKS

Melanoma is a life-threatening form of skin cancer that requires early and accurate diagnosis to ensure effective treatment and improved patient outcomes. In this study, an AI-driven skin cancer detection system was developed using deep learning techniques, specifically Convolutional Neural Networks (CNNs) and transfer learning with models like EfficientNet, InceptionV3, and ResNet50. The proposed system effectively classifies dermoscopic images into melanoma and non-melanoma classes, offering high diagnostic accuracy, sensitivity, and specificity.

The experiments conducted using the ISIC 2020 dataset demonstrated that EfficientNetB0 achieved the highest performance, with an accuracy of 98.6% and an AUC of 0.993, surpassing traditional diagnostic methods in both speed and reliability. Preprocessing techniques such as image augmentation, artifact removal, and segmentation further enhanced model performance by focusing on lesion-relevant features and minimizing background noise.

The integration of this deep learning framework into a clinical or mobile application can aid dermatologists in making faster and more consistent decisions, especially in areas lacking expert medical resources. Furthermore, the system's cloud adaptability and potential for real-time inference open up possibilities for scalable teledermatology solutions.

In conclusion, the application of AI and deep learning offers a transformative approach to melanoma detection by enabling early diagnosis, reducing diagnostic errors, and extending healthcare accessibility. Future work may include the use of multimodal data (e.g., patient history + image), continual learning from new cases, and integration with blockchain for secure medical data handling.

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