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Melanoma Detection Using Deep Learning and Image Processing

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ABSTRACT

The number of Melanoma cases has raised the need for accurate diagnostic technologies. Dermoscopic images are effectively analyzed to detect cancerous skin lesions early. Deep Learning methods assist in identifying the most important lesion features for accurate classification. In this paper, we employ Convolutional Neural Networks (CNN) for detecting melanoma and classifying it. This is helpful for dermatologists as it provides second opinion with enhanced speed and accuracy. The system closes the diagnostic gap and supports early intervention, enhancing melanoma patient outcomes.

Keywords: *Melanoma Detection, Convolutional Neural Network (CNN), Image Processing, Deep* Learning, Dermoscopy Images.

1. INTRODUCTION

Communication between doctors and patients is essential in healthcare. However, detecting melanoma, a dangerous skin cancer, through visual inspection alone is difficult, often leading to late diagnosis. To improve this, we propose an automated system for melanoma detection using image processing and deep learning techniques.

Melanoma can resemble benign lesions, making early detection challenging. Dermoscopic images, when analyzed using deep learning, help distinguish between malignant and non-malignant cases with improved accuracy. This system aims to assist dermatologists and offer faster, more consistent diagnostics.

Convolutional Neural Networks (CNNs) are widely used in medical image classification due to their ability to learn features automatically. Preprocessing steps like segmentation, contrast enhancement, and noise removal enhance image quality and boost model performance. Lightweight CNN architectures such as MobileNet are ideal for mobile deployment due to their speed and low resource usage [1].

This approach also helps extend melanoma screening to remote or underserved regions. The system provides a scalable, cost-effective solution that supports early detection and better patient outcomes.

2. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network (CNN) is a deep learning algorithm primarily used for image classification and pattern recognition tasks. It is designed to simulate the way the human visual cortex processes visual information. CNNs consist of layers of interconnected neurons that can automatically and adaptively learn spatial hierarchies of features from input images.

CNN is based on the structure of the human brain and functions similarly by processing data through layers of artificial neurons. Each neuron receives inputs, applies a transformation (like convolution), and passes the result to the next layer. These layers include convolutional layers, pooling layers, activation functions like ReLU, and fully connected layers.

In the context of melanoma detection, CNNs play a vital role in recognizing subtle patterns and features in dermoscopic images. They are capable of distinguishing between malignant and benign skin lesions with high accuracy. CNNs have proven to be highly effective in medical imaging, particularly in skin cancer detection, due to their ability to learn directly from pixel data without the need for manual feature extraction [6].

3. RELATED WORK

Many researchers have worked on melanoma detection using deep learning and image processing methods. Machine learning algorithms have been applied successfully in this domain, especially Convolutional Neural Networks (CNNs) and hybrid models, to improve classification of skin lesions and support early cancer diagnosis. These models help automate the diagnostic process, reducing human error and inter-observer variability. Additionally, lightweight and mobile-friendly architectures are enabling real-time melanoma detection even in remote and resource-limited settings.

1. “Melanalysis: A Mobile Deep Learning Approach for Early Detection of Skin Cancer” – S. A. Arani, Yu Zhang, M. Tanvir Rahman & Hui Yang (2022) Implemented EfficientNetLite-0 in a mobile application using TensorFlow Lite, with WGAN-based balanced augmentation for training. Introduced "Melanalysis", a privacy-preserving melanoma detection tool optimized for speed and low latency. Provides fast, secure, and reliable on-device melanoma detection with low latency and minimal dependence on cloud infrastructure. However, it is limited to binary classification (melanoma vs. non-

melanoma).

2. “Hybrid Deep Learning Framework for Melanoma Diagnosis Using Dermoscopic Medical Images” – Mateen, M., Yasin, A., Kanwal, N., & Ganaie, M. A. (2024). Proposed a hybrid AI framework integrating U-Net, Inception-ResNet-v2, and Vision Transformer architectures for precise melanoma classification. Developed a novel hybrid model combining CNN and Transformer techniques with a comprehensive ablation study. Achieves high accuracy by leveraging multiple state-of-the-art models and optimized feature extraction with attention mechanisms. Increased computational complexity remains a drawback due to the combination of multiple deep learning modules.

3. “Hybrid Deep Learning Framework for Enhanced Melanoma Detection” – Peng Zhang, Divya Chaudhary (2024) Combined U-Net for lesion segmentation and EfficientNet for classification, trained on HAM10000 and ISIC 2020 datasets. Proposed a hybrid model to enhance melanoma detection accuracy through segmentation and classification synergy. Achieved 99.01% classification accuracy by optimizing two powerful models. Requires large labeled datasets and substantial pretraining resources for optimal results.

4. “Deep Learning for Melanoma Detection: A Deep Learning Approach to Differentiating Malignant Melanoma from Benign Melanocytic Nevi” – Kreouzi, I., Papageorgiou, E., Skourletopoulos, G., & Vlahavas, I. (2025) Tested DenseNet121, ResNet50V2, NASNetMobile, and MobileNetV2 with augmented dermoscopic images to benchmark classification performance. Identified DenseNet121 and MobileNetV2 as top performers for accuracy and efficiency. DenseNet121 and MobileNetV2 balance performance with computational efficiency. However, static image resolution limits lesion detail and hinders classification of atypical or non-nevus lesions.

5. “Melanoma Detection Using Deep Learning-Based Classifications” – Ghadah Alwakid, Walaa Gouda (2022) Utilized ESRGAN for image enhancement, segmentation for ROI extraction, and classification via CNN and modified ResNet-50 on HAM10000. Created a hybrid system to improve lesion visibility and accuracy, validated across multiple DL architectures. Enhanced image resolution and achieved higher accuracy than prior HAM10000-based models. Dataset imbalance still affects performance despite augmentation efforts.

6. “Melanoma Detection Based on Deep Learning Networks” – S. Devaraneni (2023) Implemented ResNet-50 transfer learning with hyperparameter tuning and augmentation for melanoma image classification. Customized CNN outperformed standard MobileNetV2 and was deployed as a GUI-based web app. Achieved 91.7% accuracy with optimized hyperparameters, highlighting transfer learning’s strength. However, classification of unseen lesion types remains challenging due to limited training diversity.

7. “Developing an Efficient Method for Melanoma Detection Using CNN Techniques” – Devika Moturi, R. K. Surapaneni, and V. S. G. Avanigadda (2024) Compared MobileNetV2 with a custom CNN trained on HAM10000, deploying results via a Flask-based web app for melanoma classification. Demonstrated that the customized CNN achieved 95% accuracy and provided a user-friendly interface. Struggles with detecting lesion types not present in the

training set.

8. "Minimal Sourced and Lightweight Federated Transfer Learning Models for Skin Cancer Detection" – Vikas Khullar, Prabhjot Kaur, Shubham Gargrish, Anand Muni Mishra, Prabhishek Singh & Indrajeet Gupta (2025) Applied transfer learning with EfficientNetV2S and other lightweight models, followed by federated learning on IID and Non-IID low-resolution images. Developed a lightweight privacy-preserving melanoma detection framework for distributed environments. Performs well even on low-resolution inputs. Real-time deployment on mobile devices has yet to be achieved.

9. "Skin Cancer Detection Using Deep Machine Learning Techniques" – Olusoji Akinrinade & Chunglin Du (2024) This work applied CNN-based deep learning to raw dermoscopic images, enhanced through data augmentation and transfer learning. The authors addressed dataset class imbalance with GANs and few-shot learning, proposing a CNN framework adaptable to low-resource environments. Their approach effectively handles small and imbalanced datasets by integrating GAN-based augmentation with hybrid/ensemble modeling strategies. However, class imbalance continues to pose challenges despite augmentation techniques.

10. "Hybrid Deep Learning Model for Skin Cancer Classification" – Dr. Irala Suneetha (2024) The study proposed a hybrid architecture combining VGG16 for feature extraction and InceptionV3 for contextual learning, aiming to improve skin lesion classification accuracy. By leveraging complementary strengths of both models, the system enhances robustness and accuracy in dermoscopic image analysis. The approach benefits from improved feature diversity and classification performance, but it demands significant computational resources during both training and inference.

PAPER COMPARISION

Author(s) & Year	Dataset	Feature Extraction	Recognition Model	Accuracy
S. A. Arani, Yu Zhang, M. Tanvir Rahman & Hui Yang (2022) [1]	ISIC 2020 (44,108 images)	EfficientNetLite-0 features via CNN	ANN (EfficientNetLite-0 + TFLite)	94%
Mateen, M., Yasin, A., Kanwal, N., & Ganaie, M. A. (2024) [2]	ISIC 2020, HAM10000	Inception-ResNet-v2, Vision Transformer	Hybrid CNN + Transformer	98.65%
Peng Zhang, Divya Chaudhary (2024) [5]	HAM10000, ISIC 2020	EfficientNet-B0 + Segmentation Bridge	Deep CNN (EfficientNet-B0)	99.01%
Kreouzi, I., Papageorgiou, E., Skourletopoulos, G., & Vlahavas, I. (2025) [6]	DermNet (8,825 images)	DenseNet121, ResNet50V2, MobileNetV2	CNNs (fine-tuned with ImageNet weights)	92.30% (DenseNet121)
Ghadah Alwakid, Walaa Gouda (2022) [7]	HAM10000 (39,430 images after augmentation)	ESRGAN + Custom CNN, Modified ResNet-50	Estimated CNN model	85.98%
S. Devaraneni (2023)	ISIC archives	ResNet-50	ResNet-50 &	91.7%

[8]	(23,906 images)	(transfer learning)	custom CNN	
Devika Moturi, R. K. Surapaneni, V. S. G. Avanigadda (2024) [9]	HAM10000	MobileNetV2, custom CNN	MobileNetV2 & custom CNN	95%
Vikas Khullar, Prabhjot Kaur, Shubham Gargrish, Anand Muni Mishra, Prabhishek Singh & Indrajeet Gupta (2025) [10]	IID & Non-IID low-res images	Transfer learning (EfficientNetV2S & lightweight models)	Federated learning models	90%
Olusoji Akinrinade & Chunglin Du (2024) [3]	ISIC 2017/18, HAM10000	CNNs, ResNet-152, GANs	Hybrid CNN + ANN + Fuzzy Logic	97.51%
Dr. Irala Suneetha (2024) [4]	Kaggle (1,253 images)	VGG16 + InceptionV3	Hybrid Deep CNN	95.71%

4. CONCLUSION

Between 2020 and 2024, research on automated melanoma detection has advanced significantly, shifting from large, computation-heavy CNN architectures to lightweight, mobile-optimized models such as EfficientNetLite-0 and MobileNet, enabling real-time, on-device diagnosis. These developments have been supported by innovations in GAN-based data augmentation to address dataset imbalance, federated learning to preserve patient privacy, and ROI-based classification to improve efficiency. Hybrid deep learning approaches that combine strong feature extractors (e.g., EfficientNet, DenseNet, Vision Transformers) with segmentation networks like U-Net and preprocessing methods such as ESRGAN has pushed classification accuracy beyond 98% on benchmark datasets like HAM10000 and ISIC 2020.

Despite these promising outcomes, the field continues to face challenges related to model interpretability, generalization to diverse and unseen clinical data, and the reliable deployment of models in low-resource or mobile environments. Looking ahead, the incorporation of explainable AI methods, multimodal data fusion (combining image and clinical metadata), and privacy-aware learning strategies is likely to shape the next generation of melanoma detection systems, making them not only accurate but also trustworthy, efficient, and accessible in real-world healthcare settings.

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