2026 Volume: 02 Issue: 05 www.ijrpa.com ISSN 2456-9995 Review Article

International Journal Research Publication Analysis

Page: 01-11

A DEEP LEARNING-BASED FRAMEWORK FOR EARLY DETECTION AND CLASSIFICATION OF MELANOMA SKIN CANCER – A SURVEY

*[1]Savera Goel, [2]Rashmi Chhabra

[1]Research Scholar Department of Computer Science and Engineering South Point Institute of Technology & Management, Sonepat.

[2]Assistant Professor Department of Computer Science and Engineering South Point Institute of Technology & Management, Sonepat.

Article Received: 11 April 2026
Article Revised: 01 May 2026
Published on: 21 May 2026

***Corresponding Author: Savera Goel**
Research Scholar Department of Computer Science and Engineering South Point Institute of Technology & Management, Sonepat.

DOI: https://doi-doi.org/101555/ijrpa.9941

ABSTRACT

Melanoma skin cancer is one of the most aggressive dermatological malignancies and is associated with high mortality when diagnosis occurs at advanced stages. Early detection is therefore essential for improving patient survival and reducing treatment complexity. Recent advancements in artificial intelligence, particularly deep learning, have enabled the development of automated medical image analysis systems capable of assisting clinicians in diagnostic decision-making. This review paper examines a deep learning-based framework designed for the early detection and classification of melanoma using dermoscopic images. The framework employs convolutional neural networks (CNNs) to automatically learn hierarchical visual representations without relying on handcrafted feature extraction techniques. Preprocessing strategies such as image resizing, normalization, and data augmentation are integrated to enhance dataset diversity and improve model generalization. Experimental evaluation demonstrates exceptional classification performance, achieving an overall accuracy of 0.9978, precision of 1.000, recall of 0.9956, and F1-score of 0.9978. Confusion matrix analysis indicates 225 correctly identified melanoma cases, 224 correctly classified benign lesions, one false negative, and zero false positives. Furthermore, Receiver Operating Characteristic analysis reveals an Area Under Curve approaching unity, confirming strong discriminative capability. These findings highlight the significant potential of CNN-

based systems in supporting automated melanoma screening and improving early diagnostic outcomes.

KEYWORDS: Deep Learning, Melanoma Detection, Convolutional Neural Network, Dermoscopic Image Analysis, Skin Cancer Classification, Artificial Intelligence in Healthcare, ROC Curve, Binary Classification.

1. INTRODUCTION

Skin cancer has emerged as one of the most rapidly increasing forms of cancer worldwide, presenting a major public health concern due to rising incidence rates and associated mortality. Among the different categories of skin cancer, melanoma is widely recognized as the most aggressive and life-threatening type because of its high metastatic potential and capacity to spread quickly to distant organs. Despite representing a smaller proportion of total skin cancer cases, melanoma accounts for a significant percentage of skin cancer-related deaths. This is primarily due to delayed diagnosis and the complex nature of early lesion identification. Early detection of melanoma plays a critical role in improving survival outcomes, minimizing treatment intensity, and reducing long-term healthcare costs. When identified at an initial stage, melanoma can often be treated effectively through minimally invasive procedures, whereas advanced stages may require extensive surgical intervention, chemotherapy, or immunotherapy. Consequently, improving early diagnostic strategies remains a central objective in dermatological research and clinical practice. Traditionally, melanoma diagnosis relies on clinical visual inspection performed by dermatologists, followed by dermoscopic examination and histopathological confirmation through biopsy.

Dermoscopy enhances lesion visualization by allowing clinicians to examine subsurface skin structures and pigmentation patterns that are not easily observable with the naked eye. Although these conventional diagnostic approaches are clinically validated and widely practiced, they are inherently influenced by subjective interpretation and clinician expertise. Diagnostic accuracy may vary depending on factors such as experience level, time constraints in busy clinical environments, and variability in lesion presentation across diverse patient populations. Furthermore, distinguishing early-stage melanoma from benign skin conditions such as dysplastic nevi or seborrheic keratosis can be particularly challenging due to subtle morphological differences. These challenges often result in unnecessary biopsies, increased patient anxiety, and potential delays in treatment for missed malignant cases. Therefore, there is a growing demand for intelligent diagnostic systems capable of providing objective,

consistent, and scalable screening support. Recent advancements in artificial intelligence, especially deep learning technologies, have significantly transformed the landscape of medical image analysis. Deep learning models are capable of automatically extracting complex patterns from large volumes of high-dimensional visual data, enabling the development of automated diagnostic systems with improved predictive capability. Among various deep learning architectures, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image-related tasks such as object recognition, segmentation, and disease classification. Their hierarchical feature learning mechanism allows CNNs to identify both low-level visual characteristics, including edges and color gradients, and high-level semantic features such as lesion asymmetry, irregular borders, and heterogeneous pigmentation patterns. These attributes closely align with clinical diagnostic criteria used in melanoma detection, making CNNs particularly suitable for analysing dermoscopic images. The reviewed research focuses on the development and evaluation of a CNN-based framework designed to perform automated melanoma classification using dermoscopic image analysis. The proposed system incorporates a structured methodological pipeline consisting of image preprocessing, automated feature extraction, and binary classification. Preprocessing techniques such as image resizing, normalization, and data augmentation are employed to enhance dataset consistency and improve model generalization capability. By increasing dataset diversity and reducing overfitting, these strategies enable the neural network to learn more robust visual representations applicable to real-world clinical scenarios.

Feature learning is conducted through multiple convolutional and pooling layers that progressively transform raw image data into discriminative representations, which are subsequently processed by fully connected layers to generate probabilistic predictions regarding lesion malignancy. To ensure comprehensive performance validation, the framework evaluates classification outcomes using widely accepted medical diagnostic metrics including accuracy, precision, recall, F1-score, confusion matrix interpretation, and Receiver Operating Characteristic (ROC) curve analysis. These metrics provide a multidimensional understanding of model behaviour, particularly in terms of sensitivity to malignant lesions and reliability in distinguishing benign cases. The findings indicate that deep learning-based diagnostic frameworks can achieve highly reliable classification performance and hold substantial potential for supporting early melanoma screening initiatives. By enabling rapid and objective analysis of dermoscopic images, such systems

may assist dermatologists in improving diagnostic consistency, reducing workload, and expanding access to preventive healthcare services, particularly in resource-limited settings.

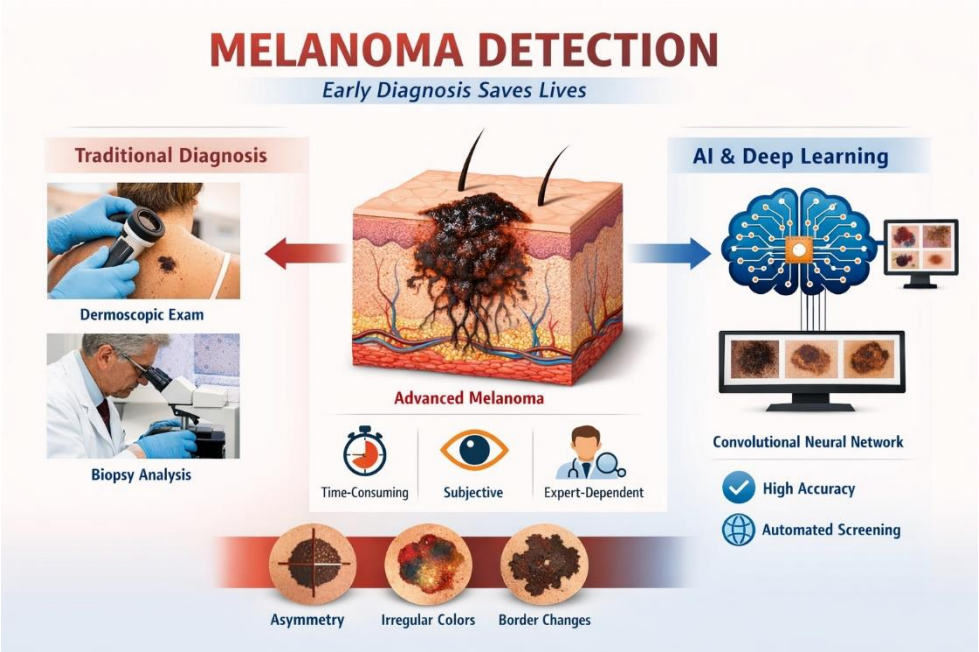

Figure 1: Conceptual Overview of Melanoma Detection Showing Comparison Between Traditional Diagnostic Methods and Deep Learning-Based Automated Screening Approaches.

2. Evolution of Automated Melanoma Detection

Automated melanoma detection has evolved significantly over the past two decades. Early research focused primarily on rule-based image processing approaches, where handcrafted features such as color histograms, shape descriptors, and texture measurements were extracted manually from dermoscopic images. These handcrafted features were then used by traditional machine learning classifiers to distinguish between benign and malignant lesions. However, these systems suffered from limited generalization capability and sensitivity to variations in imaging conditions. Subsequently, machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and decision trees were introduced to improve classification performance. These algorithms enabled data-driven learning but still relied heavily on manually engineered feature sets. As a result, their diagnostic accuracy remained constrained because handcrafted features often failed to capture the complex morphological variations associated with melanoma lesions. The emergence of deep learning fundamentally changed automated melanoma detection research. Convolutional Neural Networks enable end-to-end learning directly from raw images, allowing models to automatically extract relevant visual features. Through hierarchical convolutional layers,

CNN architectures learn both low-level image characteristics such as edges and color gradients and high-level lesion structures including irregular borders and heterogeneous pigmentation patterns.

This capability significantly improves classification accuracy and reduces reliance on manual feature engineering. Recent studies further incorporate transfer learning, attention mechanisms, and ensemble learning strategies to enhance diagnostic performance. These innovations allow models to process multi-scale visual information and improve generalization across diverse dermoscopic datasets. Consequently, deep learning-based melanoma detection systems have achieved performance levels approaching dermatologist-level diagnostic accuracy.

3. Deep Learning Framework for Melanoma Detection

The reviewed framework follows a structured pipeline designed to perform automated melanoma classification using dermoscopic image analysis. The system architecture consists of several key stages including dataset preparation, preprocessing, feature extraction, and classification.

3.1 Data Preprocessing

Data preprocessing represents a fundamental stage in the development of deep learning-based melanoma detection systems, as dermoscopic images frequently exhibit variability in quality, resolution, illumination conditions, and the presence of visual artifacts. These inconsistencies can negatively influence model training and lead to reduced classification accuracy if not appropriately addressed. Dermoscopic datasets collected from different clinical environments may include challenges such as hair occlusion, ruler markings, shadows, and uneven lighting, all of which may obscure lesion boundaries and introduce misleading patterns. Therefore, implementing structured preprocessing techniques is essential to ensure that the deep learning model receives standardized and meaningful input data.

One of the primary preprocessing operations involves image resizing, which ensures that all input images are transformed into a uniform spatial resolution suitable for batch processing within convolutional neural networks. Consistent image dimensions facilitate efficient memory utilization and prevent shape mismatches during convolutional operations. In addition to resizing, pixel intensity normalization is applied to scale image values into a standardized numerical range. This process reduces internal covariate shift and stabilizes

gradient propagation during backpropagation, enabling more effective parameter optimization. Data augmentation is another crucial component of preprocessing aimed at increasing dataset diversity and improving generalization capability. Techniques such as image rotation, horizontal and vertical flipping, zooming, and brightness adjustments are employed to simulate real-world variations in lesion presentation.

Since melanoma datasets often contain limited malignant samples compared to benign cases, augmentation helps mitigate class imbalance and reduces the risk of overfitting. Overall, systematic preprocessing enhances the robustness of the melanoma detection framework by improving data consistency, supporting stable training convergence, and enabling reliable performance across diverse dermoscopic image conditions.

3.2 Feature Extraction Using CNN

Feature extraction plays a central role in deep learning-based melanoma detection, as it determines how visual information from dermoscopic images is represented and interpreted by the classification model. Unlike traditional machine learning approaches that rely on manually engineered descriptors such as color histograms or shape metrics, convolutional neural networks automatically learn hierarchical feature representations directly from raw pixel data. This capability enables the model to identify subtle morphological characteristics associated with melanoma, including asymmetry, irregular borders, heterogeneous pigmentation, and textural abnormalities. In the proposed framework, feature extraction is achieved through multiple convolutional layers that apply learnable filters across input images. These filters respond selectively to specific visual patterns, transforming raw image inputs into increasingly abstract feature maps.

Early convolutional layers typically detect low-level visual cues such as edges, gradients, and color contrasts that provide basic structural information about skin lesions. As the network depth increases, deeper layers capture more complex and clinically relevant features, including lesion shape irregularities, multi-scale pigmentation clusters, and boundary distortions indicative of malignant transformation. Pooling layers are integrated within the feature extraction pipeline to reduce spatial dimensionality while preserving the most salient feature activations. Operations such as max pooling allow the network to focus on dominant lesion characteristics and suppress irrelevant background noise. This dimensionality reduction improves computational efficiency and enhances generalization by preventing excessive parameter growth. By automatically learning meaningful visual representations,

CNN-based feature extraction significantly improves classification accuracy and reduces reliance on domain-specific feature engineering, thereby enabling more scalable and adaptive melanoma detection solutions.

3.3 Model Architecture

The model architecture employed in the melanoma detection framework is designed to achieve reliable binary classification performance while maintaining computational feasibility. The proposed convolutional neural network structure consists of sequential convolutional layers for feature extraction, pooling layers for dimensionality reduction, fully connected dense layers for feature integration, and a sigmoid output neuron responsible for generating probabilistic predictions. This layered configuration enables the network to learn complex visual relationships within dermoscopic images and effectively distinguish between melanoma and non-melanoma lesions. Convolutional layers form the backbone of the architecture, utilizing small receptive fields to capture fine-grained lesion characteristics while preserving spatial information. Activation functions such as the Rectified Linear Unit (ReLU) introduce nonlinearity into the network, allowing it to model intricate visual patterns that cannot be represented using linear transformations alone.

Pooling layers follow convolutional operations to downsample feature maps and enhance translation invariance, ensuring that lesion classification remains robust even when lesions appear in different positions within images. Fully connected dense layers serve as the decision-making component of the network by integrating spatially distributed feature activations into a compact representation suitable for classification. To prevent overfitting and improve generalization capability, dropout regularization is incorporated within these layers. This technique randomly deactivates a subset of neurons during training, encouraging the model to learn more distributed and robust feature representations. The final sigmoid output layer produces probability values ranging from zero to one, representing the likelihood of melanoma presence. This probabilistic formulation allows threshold adjustment according to clinical screening requirements, thereby enhancing the practical applicability of the deep learning framework in real-world diagnostic environments.

4. Experimental Results and Performance Evaluation

The performance of the proposed melanoma detection framework was evaluated using multiple diagnostic metrics to ensure comprehensive analysis.

4.1 Overall Classification Performance

Experimental evaluation demonstrates that the CNN-based model achieved an overall classification accuracy of 0.9978, indicating highly reliable detection capability. Precision was reported as 1.000, meaning that all predicted melanoma cases were true malignant lesions. The recall value of 0.9956 indicates that the model successfully detected nearly all actual melanoma instances in the dataset. The resulting F1-score of 0.9978 confirms balanced classification performance between sensitivity and specificity.

4.2 Confusion Matrix Analysis

Confusion matrix evaluation provides detailed insights into class-wise prediction performance. The model correctly classified 225 melanoma cases and 224 non-melanoma cases. Only one false negative case was observed, while no false positives were recorded. These results demonstrate extremely low misclassification rates and confirm the robustness of the CNN architecture in detecting malignant lesions.

Table 1: Interpretation of Performance Metrics in Melanoma Detection.

Metric	Value Achieved	Clinical Significance	Diagnostic Impact
Accuracy	0.9978	Overall correctness of classification	Indicates highly reliable screening system
Precision	1.000	Ability to correctly identify malignant cases	Prevents unnecessary biopsies and patient anxiety
Recall (Sensitivity)	0.9956	Ability to detect actual melanoma lesions	Reduces risk of missed cancer cases
F1-Score	0.9978	Balance between precision and recall	Demonstrates stable diagnostic performance
False Negatives	1 case	Missed melanoma instance	Highlights need for continuous model improvement
ROC-AUC	≈ 1.0	Discriminative capability of classifier	Confirms strong separation between benign and malignant lesions

4.3 ROC Curve Evaluation

Receiver Operating Characteristic analysis further validates the effectiveness of the proposed framework. The ROC curve rises sharply toward the upper-left corner, indicating high true positive rates and extremely low false positive rates. The Area Under Curve (AUC) value approaches 1.0, which represents near-perfect discriminative performance. This result confirms the strong ability of the model to differentiate melanoma from benign lesions across varying classification thresholds.

5. DISCUSSION

The experimental findings highlight the effectiveness of deep learning techniques in melanoma classification. The high accuracy and balanced evaluation metrics demonstrate the ability of CNN architectures to capture both global lesion structures and subtle morphological variations associated with malignant transformation. Compared to traditional machine learning approaches, deep learning frameworks provide superior feature representation capability and improved generalization performance. The results also emphasize the importance of structured preprocessing, balanced dataset preparation, and comprehensive evaluation strategies. Data augmentation and normalization significantly contribute to model robustness by exposing the network to diverse lesion patterns. Moreover, confusion matrix analysis confirms that the system maintains reliable diagnostic sensitivity while minimizing false positive predictions. Despite these promising results, certain limitations remain. The performance of deep learning models depends heavily on dataset diversity and image quality. Real-world clinical environments may introduce additional variability that could affect classification performance. Therefore, further validation using multi-institutional datasets and prospective clinical studies is necessary before large-scale clinical deployment.

6. CONCLUSION

This review has examined a deep learning-based framework developed for the early detection and classification of melanoma skin cancer using dermoscopic image analysis. The findings highlight the significant potential of convolutional neural network architectures in improving diagnostic accuracy and supporting automated medical image interpretation. The proposed framework demonstrates exceptionally high classification performance, achieving an overall accuracy of 0.9978, precision of 1.000, recall of 0.9956, and an F1-score of 0.9978. Confusion matrix evaluation further confirms the reliability of the model, indicating 225 correctly identified melanoma cases and 224 accurately classified benign lesions, with only a minimal rate of misclassification. In addition, Receiver Operating Characteristic analysis reveals near-perfect discriminative capability, with the Area Under Curve approaching unity, thereby validating the robustness of the probabilistic classification approach.These results emphasize the transformative role of deep learning in enhancing dermatological diagnostics by enabling objective, consistent, and scalable screening solutions. Automated melanoma detection systems have the potential to assist clinicians in early lesion identification, reduce diagnostic variability, and optimize healthcare resource utilization. However, despite promising experimental performance, challenges related to dataset diversity, model

generalization, and clinical interpretability remain important considerations for real-world deployment. Future research should focus on incorporating multimodal clinical data, improving cross-dataset validation strategies, and designing computationally efficient architectures suitable for real-time applications and teledermatology platforms. Strengthening interdisciplinary collaboration between artificial intelligence researchers and medical practitioners will be essential for translating these technological advancements into clinically effective diagnostic tools that improve patient outcomes and support preventive healthcare initiatives.

REFERENCES

1. Islam, S. et al. (2026). *Advancing skin cancer detection through deep learning using multimodal patient metadata and dermoscopic imaging.* Scientific Reports. (Nature)
2. Nawaz, K. et al. (2025). *Skin cancer detection using dermoscopic images with convolutional neural networks.* Scientific Reports. (Nature)
3. Yao, Y. et al. (2025). *Advancing skin cancer diagnosis with ConvNeXtV2 and focal self-attention frameworks.* Scientific Reports. (Nature)
4. Lallas, K. et al. (2025). *Machine learning algorithms using dermatoscopy for melanoma prognosis.* ScienceDirect. (ScienceDirect)
5. Górecki, S. et al. (2025). *Artificial intelligence and new technologies in melanoma diagnosis: A systematic review.* PMC. (PMC)
6. Kreouzi, M. et al. (2024). *Deep learning for melanoma detection using CNN architectures.* PMC. (PMC)
7. Alotaibi, A. et al. (2025). *Transfer learning with attention mechanisms for skin cancer classification.* PMC. (PMC)
8. Babu, R. R. & Philip, F. M. (2024). *Optimized deep learning for dermoscopic lesion segmentation and detection.* Springer. (Springer)
9. Al-Waisy, A. S. et al. (2025). *Deep learning framework for automated early diagnosis of skin cancer.* Scientific Reports. (Nature)
10. Öznacar, T. et al. (2025). *Advanced skin cancer prediction with medical image deep learning models.* Scientific Reports. (Nature)
11. Subramanian, M. et al. (2025). *Attention-aware deep learning models for dermoscopic image classification.* PMC. (PMC)
12. Akinrinade, O. et al. (2025). *Skin cancer detection using deep machine learning techniques.* ScienceDirect. (ScienceDirect)

13. Jaber, N. J. F. et al. (2024). *Robust CNN-based melanoma image classification using ISIC dataset.* Springer Multimedia Tools. (Springer)
14. Nawaz, K. et al. (2025). *FCDS-CNN model for imbalanced melanoma datasets.* PMC. (PMC)
15. Mateen, M. et al. (2024). *Hybrid deep learning framework using U-Net and Vision Transformer for melanoma diagnosis.* MDPI Diagnostics. (MDPI)
16. Haque, S. et al. (2025). *Deep learning approaches for skin cancer detection: A literature synthesis.* SAGE Journals. (SAGE Journals)
17. Da Costa Nascimento, J. J. et al. (2024). *Health-of-Things melanoma detection system using AI and cloud computing.* Frontiers. (Frontiers)
18. Alam, F. et al. (2025). *Artificial intelligence in melanoma detection: Advances and challenges.* Wiley. (Wiley Online Library)
19. Krishna, S. R. et al. (2024). *Deep learning model for dermoscopic skin lesion identification.* JAIT. (ojs.istp-press.com)
20. Huang, Q. et al. (2023). *Computer-aided skin cancer diagnosis using deep learning and metaheuristics.* Computers in Biology and Medicine. (ScienceDirect)
21. Panneerselvam, R. et al. (2025). *Multimodal skin cancer prediction integrating clinical metadata and dermoscopy.* Open Bioinformatics Journal. (The Open Bioinformatics Journal)
22. Furriel, B. C. R. S. et al. (2024). *Artificial intelligence for skin cancer detection: Systematic review in clinical settings.* Frontiers in Medicine. (Frontiers)
23. Kandhro, I. A. et al. (2024). *Performance evaluation of enhanced VGG-based deep learning model for real-time skin cancer detection.* Heliyon. *(mentioned within recent comparative studies)* (Nature)
24. Naeem, A. et al. (2024). *SNC-Net hybrid deep learning framework for dermoscopic lesion classification.* Mathematics (MDPI). (Nature)
25. Zhang, L. et al. (2024). *GRU-based deep learning approach for prompt skin cancer detection.* Biomedical Signal Processing and Control. (Nature)