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A Thorough Analysis of Deep Learning-Based Early Melanoma Detection

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Abstract: *Melanoma is one of the most aggressive and life-threatening forms of skin cancer, posing a major challenge to global healthcare due to its rapid progression and high mortality rates when diagnosis is delayed. Conventional diagnostic methods primarily depend on clinical observation and dermatologist expertise, which can often be subjective and inconsistent. In recent years, deep learning—particularly Convolutional Neural Networks (CNNs)—has shown strong potential to enhance diagnostic accuracy by automatically identifying subtle variations in dermoscopic images that may not be easily recognized by the human eye. This study presents a CNN-based framework for the early detection of melanoma using transfer learning with the ResNet50 architecture. The research employs the HAM10000 dataset, which contains over 10,000 dermoscopic images representing seven different skin lesion categories. Prior to training, the dataset undergoes normalization and data augmentation to improve image quality and model generalization. The ResNet50 network is fine-tuned by replacing its fully connected layers with custom dense, dropout, and sigmoid layers, optimized using the Adam optimizer and binary cross-entropy loss function. The proposed approach delivers a reliable, non-invasive, and efficient diagnostic support system to assist dermatologists in early melanoma recognition. By combining transfer learning and augmentation, the model improves classification accuracy and reduces dependency on manual feature extraction. Overall, this work highlights the promise of deep learning in dermatological diagnostics and lays the groundwork for future research on explainable models and clinical validation in real-world medical settings.*

Keywords: Convolutional neural networks (CNNs), deep learning, image classification, skin cancer detection, melanoma, and the HAM10000 dataset

I. INTRODUCTION

Melanoma, while not the most prevalent skin cancer, is globally recognized as the deadliest form, necessitating advanced diagnostic approaches (Albahli, 2025; Virgens et al., 2025). The aggressive nature of melanoma, coupled with its propensity to infiltrate surrounding tissues, contributes to its high mortality rate (Kavitha et al., 2024). Early and accurate detection is paramount for improving patient outcomes and reducing the mortality associated with this malignancy (Kalidindi, 2024; Patel et al., 2023). Traditional diagnostic methods, including visual inspection and dermoscopy, are heavily reliant on the subjective expertise of dermatologists, which can lead to significant inter-observer variability (Kreouzi et al., 2024). This subjectivity underscores the urgent need for more objective, efficient, and precise diagnostic tools, especially given the rising incidence of skin cancer globally. Artificial intelligence, particularly deep learning, has emerged as a transformative technology in medical diagnostics, offering promising solutions for automating and enhancing the accuracy of melanoma detection. The application of deep learning to medical imaging, specifically dermoscopic analysis, has shown significant potential in differentiating malignant melanoma from benign skin lesions, thereby reducing the burden on clinical experts and improving diagnostic throughput. This advancement is critical because early detection of skin cancer significantly increases the chances of successful treatment and prevents metastasis to other organs. Consequently, the development of automated models for early melanoma diagnosis is crucial for mitigating disease severity and facilitating prompt therapeutic interventions.

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Indeed, projections suggest that melanoma is poised to become the second most prevalent cancer by 2040, thereby intensifying the imperative for enhanced early diagnostic methodologies.

One of the most common malignancies in the world is skin cancer. Melanoma is one of the most dangerous varieties. Melanoma grows quickly and can spread to other regions of the body, unlike other skin cancers, therefore early detection is crucial. Extended exposure to ultraviolet (UV) radiation from the sun is the main cause of melanoma. However, because skin lesions vary in size, color, texture, and uneven borders, early identification is still difficult. Using instruments like dermoscopy and magnifying lenses, dermatologists have traditionally used visual inspection to detect melanoma. Nevertheless, this procedure takes a lot of time and is highly dependent on the clinician's experience. Even small variations in color, size, texture, or shape of a skin lesion can make diagnosis difficult and maylead tohuman error.

Automated skin cancer detection has received a lot of interest thanks to developments in deep learning, namely Convolutional Neural Networks (CNNs). CNN models eliminate the need for manual feature extraction by learning intricate visual patterns from dermoscopic images, including texture, color, form, and uneven borders.

Melanoma and non-melanoma skin lesions are classified in this study using a CNN-based method that uses transfer learning using the ResNet50 architecture. The model is trained using the HAM10000 dataset, which includes 10,015 dermoscopic pictures of different kinds of skin lesions. The goal of the suggested system is to give dermatologists a non-invasive, precise, and effective diagnostic tool to help in melanoma early detection.

II. LITERATURE REVIEW AND RESEARCH GAPS

Recent advancements in deep learning have substantially improved the early detection of melanoma, primarily due to the ability of Convolutional Neural Networks (CNNs) to automatically learn discriminative features from dermoscopic images. A wide range of CNN-based and hybrid models have been proposed to enhance diagnostic accuracy while reducing reliance on manual feature extraction.

Jojoa Acosta et al. (2021) proposed a two-stage melanoma detection framework that combined Mask R-CNN for lesion localization and ResNet152 for classification. Evaluated on the ISIC 2017 dataset, the model achieved strong performance in terms of accuracy, sensitivity, and specificity, demonstrating effective discrimination between malignant and benign lesions. Garcia et al. (2021) explored a meta-learning approach to address limited annotated medical data. By fine-tuning a ResNet50 model pre-trained on ImageNet using a small medical dataset, the study demonstrated significant improvements in segmentation performance, highlighting the potential of transfer learning for data-scarce scenarios. Alheejawi et al. (2021) focused on histopathological image analysis and introduced INS-Net for melanoma region segmentation in H&E-stained whole slide images. Their approach achieved high segmentation accuracy for both nuclei and melanoma regions, demonstrating the effectiveness of specialized CNN architectures in histopathology-based diagnosis.

Yu et al. (2022) introduced a novel framework for early melanoma diagnosis using sequential dermoscopic images. By aligning follow-up images and employing a spatio-temporal network, their model effectively captured lesion evolution over time and outperformed experienced clinicians in diagnostic accuracy on a serial image dataset. Musthafa et al. (2024) proposed an optimized CNN architecture for melanoma classification using the HAM10000 dataset. Through data augmentation and model optimization techniques, the model achieved high accuracy, precision, and recall, demonstrating the effectiveness of architectural tuning for static dermoscopic images. Moturi et al. (2024) compared a custom CNN model with MobileNetV2 for melanoma detection and demonstrated superior performance of the custom architecture. The best-performing model was integrated into a web-based application, emphasizing practical deployment and real-world usability.

Esmaeili et al. (2025) developed an optimized five-stream CNN framework incorporating extensive preprocessing and multiple feature extraction pathways. The model achieved exceptionally high accuracy across benchmark datasets such as HAM10000 and ISIC 2024, highlighting the potential of multi-stream architectures for melanoma detection. Azhari et al. (2025) proposed a two-stage CNN framework in which weakly supervised segmentation using Grad-CAM guided a second-stage classifier.

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The approach improved classification performance compared to single-stage models, demonstrating the benefits of incorporating attention mechanisms.

Despite significant progress in melanoma detection using deep learning, several critical gaps remain evident from the literature. Most existing models rely on static dermoscopic images, neglecting the clinically important temporal evolution of skin lesions. Although spatio-temporal frameworks have been explored, they have largely been validated on small or proprietary datasets, limiting their generalizability.

Additionally, many high-performing models report exceptionally high accuracy on benchmark datasets, raising concerns about overfitting and insufficient validation on external clinical data. Weakly supervised segmentation techniques, while computationally efficient, often generate coarse lesion boundaries, potentially limiting classification performance. Furthermore, limited attention has been given to integrating robust segmentation with classification and to developing models that balance high diagnostic accuracy with real-world applicability and interpretability.

Early and accurate detection of melanoma remains a critical clinical challenge due to the visual similarity between malignant and benign skin lesions and the dynamic nature of lesion evolution over time. Although deep learning–based models have demonstrated high accuracy on static dermoscopic images, existing approaches often fail to incorporate temporal lesion changes, rely on weakly supervised or coarse segmentation, and lack validation across diverse, large-scale clinical datasets. These limitations restrict the robustness, generalizability, and clinical reliability of current automated melanoma diagnostic systems.

The primary objectives of the present study are: To develop an automated deep learning–based framework for melanoma detection using dermoscopic images. To incorporate accurate lesion segmentation to enhance feature localization and classification performance. To investigate the diagnostic benefits of integrating temporal or sequential lesion information, where available. To evaluate the proposed model on publicly available benchmark datasets to ensure robustness and generalizability. To compare the performance of the proposed framework with existing state-of-the-art methods using standard evaluation metrics. To assess the feasibility of the developed model for real-world clinical screening applications.

III. METHODOLOGY

Based on the reviewed research papers and the objectives of this study, the proposed methodology focuses on developing an efficient andreliabledeeplearningmodel for earlymelanoma detection usingConvolutional Neural Networks(CNNs).Theprocess comprises four main stages: dataset collection, preprocessing andaugmentation, model design and training, and evaluation.

Overview

This study explores the application of deep learning techniques for the detection of melanoma from dermoscopic images. The approach involves selecting a suitable dataset, performing necessary preprocessing steps, applying data augmentation techniques, and training a CNN model through transfer learning. A pre-trained model, ResNet50—originallytrained on theImageNet dataset— isfine-tunedtorecognizemelanoma-specificvisualpatternsin skin lesions. Thismethodleveragespreviouslylearnedlow-leveland mid-level image features, allowing faster convergence and improved performance even with limited medical image data.

Dataset Description

The HAM10000 (“Human Against Machine with 10,000 training images”) dataset is employed in this study. It is one of the most widely used benchmarks for skin lesion classification and contains approximately 10,015 dermoscopic images distributed across seven distinct lesion categories: Actinic Keratoses (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic Nevi (NV), and Vascular Lesions (VASC). The dataset represents diverse patient demographics and varying lesion appearances. Each image has been verified through histopathology, expert consensus, or follow-up examination, ensuringhigh-qualityand clinicallyvalidated data suitable for model training, validation, and testing.

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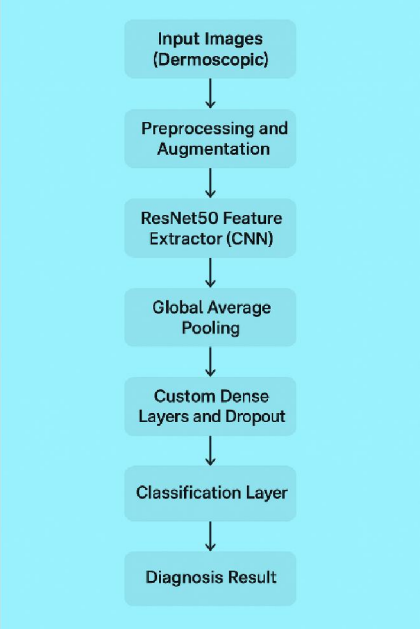

Fig. 1. Dermoscopic Image Analysis Workflow

Data Preprocessing

Before training, several preprocessing operations are performed to standardize the dataset and enhance the model's learning efficiency. All images are resized to 224 × 224 pixels to matchthe input dimensions required by ResNet50. Pixel intensity values arenormalized totherange[0,1]tostabilizegradientupdatesandspeed up convergence. Optional artifactremoval techniques, such as hair and noise filtering, are applied toreduce unwanted visual elements that mayinterfere with lesion analysis.

To prevent overfitting and improve generalization, data augmentation techniques such as random rotations, flips, zooming, and brightness adjustments are implemented. This not only increases the dataset's variability but also enables the model to perform effectively on unseen test samples.

Model Architecture and Training

A CNN-based modelwith transfer learning is implemented using the ResNet50 architecture. Instead of training from scratch, thetop classification layers of ResNet50—originally designed for 1,000 ImageNet categories—are replaced with task-specific layers optimized for binary classification of melanoma and non-melanoma lesions.

The modified architecture includes:

- A Global Average Pooling layer to reduce dimensionality and retain essential spatial features.
- A Dense layer with 128 neurons and ReLU activation to capture complex feature representations.
- A Dropout layer to prevent overfitting by randomly deactivating neurons during training.
- A final Dense layer with a single neuron and sigmoid activation to output the probability of melanoma.
- The model is compiled using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function.

The dataset is split into 70% training, 20% validation, and 10% testing subsets. Initially, the lower convolutional layers of ResNet50 are kept frozen to preserve generic image representations. In later stages, selected higher layers are unfrozen and fine-tuned to adapt to melanoma-specific features. Training is carried out for 10–20 epochs with a batch size of 32. Techniques such as early stopping and model checkpointing are employed to prevent overfitting and retain the best-performing weights.

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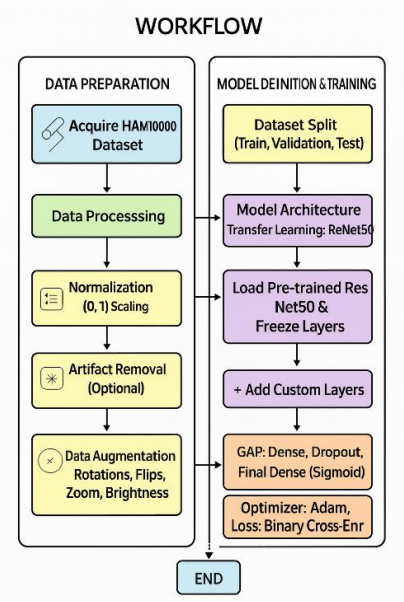

Fig. 2. Melanoma CNN Workflow

Evaluation

After training, the model's performance is evaluated on the test dataset using multiple metrics to ensure comprehensive assessment.

- Accuracy measures the overall correctness of predictions.
- Precision indicates the proportion of correctly predicted melanoma cases among all positive predictions.
- Recall (Sensitivity) reflects the model's ability to correctly identify actual melanoma cases.
- F1-Score provides a balanced evaluation by combining precision and recall.
- ROC-AUC measures the model's ability to distinguish between melanoma and non-melanoma classes. Additionally, a Confusion Matrix is used to visualize classification results and identify misclassified samples.

This multi-stage methodology aims to deliver a robust, non-invasive, and clinically useful diagnostic system capable of assisting dermatologists in early melanoma detection with improved accuracy and reliability.

IV. CONCLUSION

This study highlights the growing impact of deep learning–based techniques in the automated detection of melanoma, demonstrating their effectiveness in extracting discriminative features from dermoscopic images. CNN-based models, particularly those leveraging transfer learning with architectures such as ResNet50, have achieved high accuracy on standard benchmark datasets, underscoring their potential as supportive diagnostic tools in dermatology.

Despite these advancements, significant challenges remain, including the reliance on static image analysis and limited validation in real-world clinical settings. Addressing these limitations through the integration of temporal lesion analysis, improved dataset diversity, and enhanced model generalization is essential for further progress. Additionally, increasing model interpretability and ensuring robust cross-dataset evaluation will be critical for clinical adoption. Overall, the continued development and responsible deployment of deep learning–driven diagnostic systems can play a vital role in supporting dermatologists, enabling earlier melanoma detection, and improving patient survival outcomes.

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