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Early Melanoma Detection Using Deep Learning: A Comprehensive Review

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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.

Index Words: Skin Cancer Detection, Melanoma, Image Classification, Deep Learning, Convolutional Neural Network (CNN), HAM10000 dataset.

I. INTRODUCTION

Skin cancer is among the most frequently occurring cancers worldwide. Among its various types, melanoma is one of the most dangerous forms. Unlike other skin cancers, melanoma grows rapidly and can spread to other parts of the body, making early detection extremely important. The primary cause of melanoma is prolonged exposure to ultraviolet (UV) radiation from the sun. However, early detection remains challenging due to variations in the color, texture, size, and irregular borders of skin lesions.

Traditionally, dermatologists identify melanoma through visual inspection using tools such as magnifying lenses and dermoscopy. However, this process is time-consuming and heavily depends on the experience of the clinician. Even small variations in color, size, texture, or shape of a skin lesion can make diagnosis difficult and may lead to human error.

With advancements in deep learning, particularly Convolutional Neural Networks (CNNs), automated skin cancer detection has gained significant attention. CNN models can learn complex visual patterns such as texture, color, shape, and irregular borders from dermoscopic images, reducing the need for manual feature extraction.

In this study, a CNN-based approach using transfer learning with the ResNet50 architecture is implemented for the classification of melanoma and non-melanoma skin lesions. The HAM10000 dataset, which contains 10,015 dermoscopic images of various types of skin lesions, is used to train the model. The proposed system aims to provide a non-invasive, accurate, and efficient diagnostic tool to assist dermatologists in the early detection of melanoma.

II. LITERATURE REVIEW AND RESEARCH GAPS

In recent years, deep learning–based approaches have significantly contributed to the early detection of melanoma, primarily due to their ability to automatically extract discriminative visual features from dermoscopic images. Numerous researchers have developed Convolutional Neural Network (CNN) architectures and hybrid models capable of classifying skin lesions with high accuracy and minimal manual intervention.

Melanoma Diagnosis Using Deep Learning Techniques on Dermatoscopic Images (2021) by Jojoa Acosta, M. F., et al. introduced a two-step approach for melanoma detection. In the first step, the model utilizes Mask R-CNN for automatic cropping of the lesion, and in the second step, it employs a ResNet152 classifier on the cropped region. Tested on the ISIC 2017 challenge dataset, the model achieved an accuracy of 90.4%, with a sensitivity of 82.0% and a specificity of 92.5%. The method demonstrated superior performance in identifying true positives and true negatives compared to other models in the competition.

Research Gap: This method analyzes lesions at a single point in time, overlooking the diagnostic value of monitoring lesion changes longitudinally.

Meta-Learning for Skin Cancer Detection Using Deep Learning Techniques (2021) by Garcia, S. I. explored a meta-learning strategy to address the issue of data scarcity. A ResNet50 model, pre-trained on the non-medical ImageNet dataset, was retrained using a small, combined medical dataset containing 193 images. The study found that this transfer of knowledge from a non-medical domain increased the Jaccard Similarity Index by 20 points, with the proposed class-balancing algorithm adding an additional 5-point improvement.

Research Gap: Although the meta-learning concept is promising for limited-data scenarios, its effectiveness must be validated on larger and more diverse medical datasets to ensure scalability and robustness.

An Efficient CNN-Based Algorithm for Detecting Melanoma Cancer Regions in H&E-Stained Images (2021) by Alheejawi, S., et al. focused on histopathological image analysis. The authors developed a novel deep learning architecture, INS-Net, for segmenting cell nuclei, followed by morphological operations to outline melanoma regions. On their custom dataset of Whole Slide Images (WSIs), the technique achieved a melanoma region segmentation accuracy of 97.7% and a nuclei segmentation accuracy of 94.12%.

Research Gap: The methodology is specialized for H&E-stained histopathological images. A significant gap exists in adapting these high-precision segmentation techniques for use with dermoscopic images, which are more commonly employed during initial clinical screenings.

Early Melanoma Diagnosis with Sequential Dermoscopic Images (2022) by Yu, Z., et al. pioneered the use of sequential images for temporal lesion analysis. Their framework aligns follow-up images of a lesion to capture temporal changes and employs a spatio-temporal network to model lesion evolution. On a proprietary dataset of 179 serial image sequences, the model surpassed the diagnostic accuracy of 12 clinicians (63.69% vs. 54.33%) and diagnosed melanoma earlier in a greater percentage of cases.

Research Gap: This groundbreaking use of sequential data must be validated on large-scale, publicly available datasets to confirm the generalizability and reliability of the spatio-temporal framework.

Enhanced Skin Cancer Diagnosis Using Optimized CNN Architecture (2024) by Musthafa, M. M., et al. proposed an optimized CNN model utilizing the HAM10000 dataset. Their model incorporated data augmentation and a model checkpoint callback for optimization, achieving a high accuracy of 97.78%, with both precision and recall reaching 97.9%.

Research Gap: The architecture is optimized for static images. Future work could extend this model into a spatio-temporal framework to incorporate the diagnostic benefits of lesion evolution analysis.

Developing an Efficient Method for Melanoma Detection Using CNN Techniques (2024) by Moturi, D., et al. focused on practical implementation. The authors compared a customized CNN model with MobileNetV2 using the HAM10000 dataset. The custom CNN achieved superior accuracy (95%) compared to MobileNetV2 (85%). The better-performing model was then integrated into a Flask-based web application for user interaction.

Research Gap: This work primarily compares existing architectures for practical deployment rather than proposing novel architectural advancements or exploring new diagnostic paradigms such as temporal or multimodal analysis.

Automatic Melanoma Detection Using an Optimized Five-Stream Convolutional Neural Network (2025) by Esmaeili, V., et al. developed a comprehensive system incorporating extensive preprocessing and four distinct feature extractors feeding into a five-stream CNN. The model achieved exceptionally high accuracies across multiple datasets—99.8% on HAM10000 and 99.9% on ISIC 2024.

Research Gap: While these results are remarkable, they require validation on external, unseen clinical datasets to ensure generalizability and to verify that the model is not overfitted to benchmark data characteristics.

Two-Stage CNN with Weakly Supervised Segmentation for Skin Lesion Classification (2025) by Azhari, A. A., et al. proposed a two-stage CNN framework for skin lesion classification. In the first stage, Grad-CAM was used to generate attention maps for lesion segmentation, which then guided a second, more focused classification stage. This approach achieved 96.2% accuracy on the HAM10000 dataset, outperforming a single-stage model.

Research Gap: The segmentation process is “weakly supervised” using Grad-CAM, which generates coarse attention maps rather than precise boundaries. There is a clear opportunity to integrate a fully supervised segmentation method to further enhance classification accuracy.

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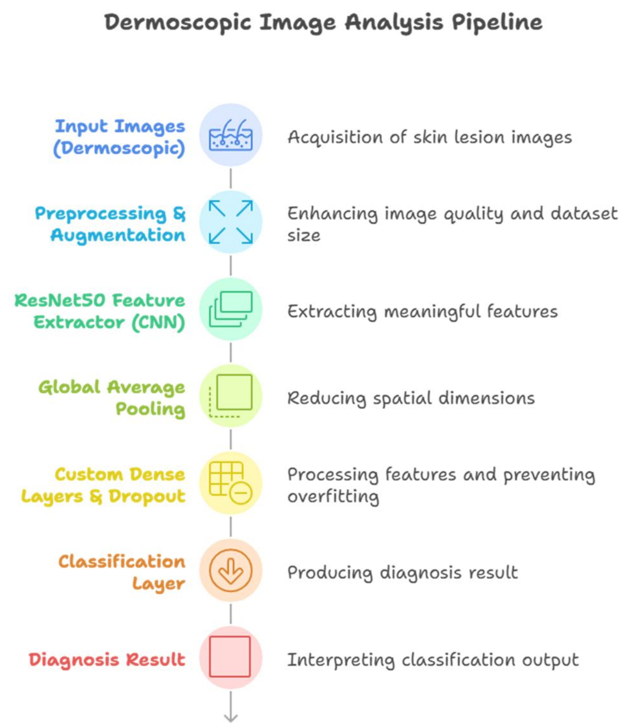
III. METHODOLOGY

Based on the reviewed research papers and the objectives of this study, the proposed methodology focuses on developing an efficient and reliable deep learning model for early melanoma detection using Convolutional Neural Networks (CNNs). The process comprises four main stages: dataset collection, preprocessing and augmentation, model design and training, and evaluation.

A. 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—originally trained on the ImageNet dataset—is fine-tuned to recognize melanoma-specific visual patterns in skin lesions. This method leverages previously learned low-level and mid-level image features, allowing faster convergence and improved performance even with limited medical image data.



B. 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, ensuring high-quality and clinically validated data suitable for model training, validation, and testing.

C. 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 match the input dimensions required by ResNet50. Pixel intensity values are normalized to the range [0, 1] to stabilize gradient updates and speed up convergence. Optional artifact removal techniques, such as hair and noise filtering, are applied to reduce unwanted visual elements that may interfere 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.

D. Model Architecture and Training

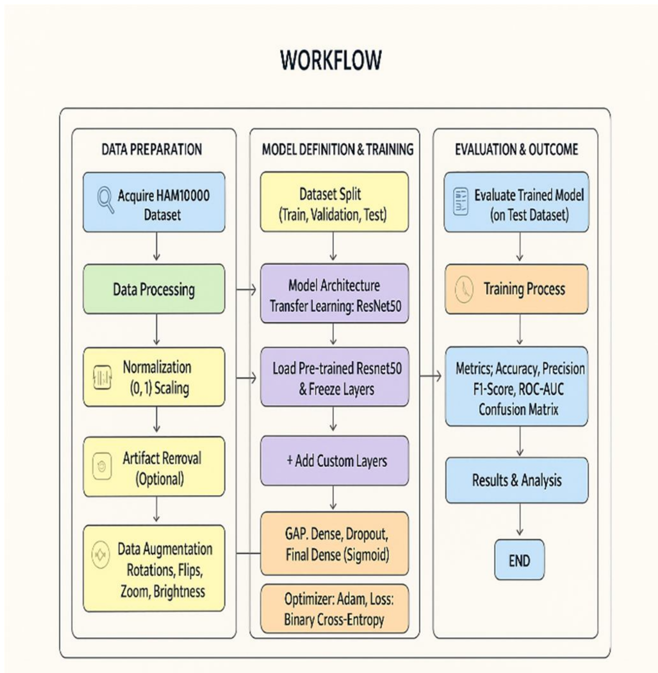
A CNN-based model with transfer learning is implemented using the ResNet50 architecture. Instead of training from scratch, the top classification layers of ResNet50—originally designed for 1,000 ImageNet categories—are replaced with task-specific layers optimized for binary classification of melanoma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



E. 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

Early and accurate detection of melanoma remains a critical factor in improving patient survival rates and reducing the global burden of skin cancer. This review highlights the increasing role of deep learning, particularly Convolutional Neural Networks (CNNs), as a dependable diagnostic aid in dermatology.

By automatically identifying intricate visual patterns such as color, texture, and lesion borders, CNN-based models address many of the limitations associated with manual diagnosis and inter-observer variability. Among existing architectures, transfer learning techniques using advanced networks like ResNet50 and hybrid CNN models have consistently demonstrated high accuracy and robustness on benchmark datasets such as HAM10000 and ISIC.

Despite these promising advances, certain research gaps remain. Most existing systems rely solely on static dermoscopic images and do not account for temporal lesion changes—an important factor for early-stage melanoma detection. Furthermore, while many models show strong performance on benchmark datasets, their effectiveness in real-world clinical settings requires further validation. Expanding dataset diversity, incorporating temporal and multimodal learning frameworks, and improving model generalization could significantly enhance diagnostic reliability.

In summary, deep learning continues to transform the field of melanoma detection by offering efficient, scalable, and non-invasive diagnostic solutions. The integration of these intelligent systems into clinical workflows can provide valuable support to dermatologists, leading to earlier intervention and improved patient outcomes. Future research should focus on enhancing model transparency, cross-dataset validation, and clinical decision-support integration to ensure the safe, ethical, and effective adoption of AI-driven diagnostic systems in healthcare practice.

V. ACKNOWLEDGEMENT

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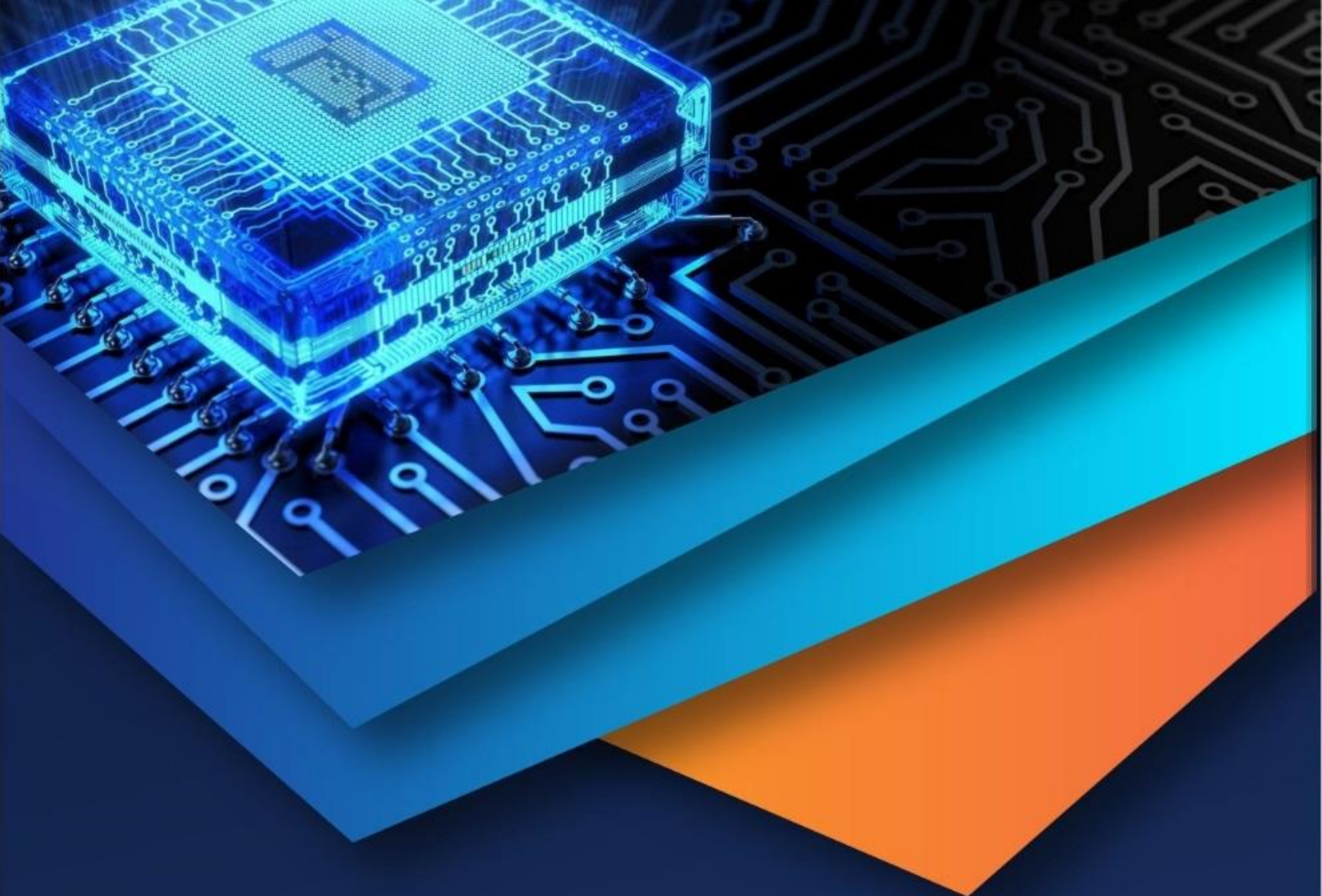

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