ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

DermAnalyze AI: A Gatekeeper-Driven Severity-Aware Skin Disease Classification Framework Using Lightweight Deep Learning for Mobile Healthcare

Vanitha Muthu P.[1]; Bhuvaneswari C.[2]; Meenushree R.[3]; Rajasri R.[4]; Vinisha E.[5]

[1,2,3,4,5] Department of Computer Science and Engineering,
Government College of Engineering Srirangam,
Tiruchirappalli – 620012, Tamil Nadu, India

Publication Date: 2026/04/28

Abstract: Accurate and timely diagnosis of skin diseases is essential for enabling early treatment, reducing healthcare costs, and improving patient outcomes. Conventional diagnostic approaches rely on manual visual inspection by dermatologists, which can be subjective, time-consuming, and often inaccessible in remote or resource-limited settings. This paper presents DermAnalyze AI, a multi-stage framework that integrates image processing with lightweight deep learning for effective skin disease classification and severity estimation. The proposed system incorporates a novel gatekeeper mechanism that initially verifies whether the input image contains human skin using colour-space filtering, thereby rejecting irrelevant or low-quality inputs and ensuring diagnostic integrity. For validated inputs, a MobileNetV2-based architecture is employed for efficient feature extraction and classification of various skin conditions. In addition, a dedicated severity analysis module computes a quantitative severity index, categorizing cases into mild, moderate, and severe levels. This severity-aware design extends beyond conventional classification by providing clinically interpretable insights and supporting treatment recommendations. Experimental evaluation on the HAM10000 dataset demonstrates that the proposed model achieves an accuracy of 93.2% and a weighted F1-score of 0.92, indicating robust classification performance across multiple disease categories. Furthermore, the lightweight architecture ensures reduced computational complexity and faster inference, making it suitable for deployment in mobile and resource-constrained environments. Overall, the proposed framework offers a scalable, reliable, and accessible solution for real-world dermatological screening.

Keywords: *Skin Disease Classification, Severity Estimation, Deep Learning, MobileNetV2, Medical Image Analysis, Computer Vision, HAM10000 Dataset, Clinical Decision Support, Lightweight Neural Networks, Mobile Healthcare*

How to Cite: Vanitha Muthu P.; Bhuvaneswari C.; Meenushree R.; Rajasri R.; Vinisha E. (2026) DermAnalyze AI: A Gatekeeper-Driven Severity-Aware Skin Disease Classification Framework Using Lightweight Deep Learning for Mobile Healthcare. *International Journal of Innovative Science and Research Technology*, 11(4), 2220-2226. https://doi.org/10.38124/ijisrt/26apr1153

I. INTRODUCTION

The healthcare sector continues to face significant challenges in the early detection and effective management of dermatological conditions. A considerable proportion of global health complications arises from delayed diagnosis and the limited availability of specialised dermatological care, particularly in rural and resource-constrained regions. Accurate and reliable evaluation of skin lesions is therefore essential to prevent the progression of malignant conditions, reduce treatment costs, and improve patient survival outcomes [7], [15].

Traditionally, skin disease diagnosis has relied on manual visual examination by dermatologists. Although widely practised, this approach is inherently subjective, time-intensive, and susceptible to variability due to human error and judgment fatigue. The high morphological similarity among different skin lesions further complicates accurate diagnosis. Moreover, conventional image analysis techniques based on handcrafted features often fail to generalise effectively under real-world conditions, where variations in illumination, skin tone, and complex textures are prevalent. These limitations reduce the reliability and scalability of traditional diagnostic systems [3], [5].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

Recent advances in data-driven methodologies, particularly deep learning, have significantly enhanced the capabilities of medical image analysis. Deep learning models can automatically learn complex visual representations from dermoscopic images, leading to improved diagnostic consistency and accuracy compared to manual approaches [2], [3], [13]. Several studies have demonstrated high-performance skin disease classification using convolutional neural networks and transfer learning techniques [1], [4], [7]. However, most existing methods are primarily focused on disease classification and provide only categorical outputs, without addressing the critical aspect of clinical severity or offering actionable recommendations for treatment [4], [8]. This limitation restricts their practical applicability in real-world clinical decision-making.

To overcome these limitations, this work proposes DermAnalyze AI, a multi-stage framework for skin disease classification and severity-aware prediction. The proposed system introduces a Skin-Tone Gatekeeper module that validates whether the input image contains human skin using YCbCr colour-space filtering. Invalid or low-quality inputs are rejected at this stage, thereby ensuring diagnostic integrity and improving overall system efficiency. For validated inputs, a lightweight MobileNetV2 architecture is employed to perform disease classification, leveraging efficient deep learning principles [11]. The model is trained and evaluated using the HAM10000 dataset, which provides diverse dermoscopic images for robust learning [6], [9].

Following classification, a severity estimation module computes a quantitative index based on lesion texture and spatial distribution. Based on this index, the system categorises the condition into three clinically relevant tiers: mild, moderate, and severe, and provides objective insights along with treatment recommendations. The proposed approach is designed with a strong emphasis on accessibility, enabling deployment on mobile platforms to support real-time dermatological screening. By integrating input validation, efficient deep learning, and severity-aware analysis, the framework contributes to improving diagnostic accuracy, enhancing usability, and reducing the burden on healthcare infrastructure, thereby supporting more effective and scalable dermatological care.

The main contributions of this work are summarised as follows:

- A novel multi-stage framework, DermAnalyze AI, for integrated skin disease classification and severity estimation.
- A Skin-Tone Gatekeeper mechanism for input validation using YCbCr colour-space filtering to improve diagnostic reliability.
- A lightweight MobileNetV2-based architecture for efficient and accurate classification suitable for mobile deployment [11].
- A severity-aware analysis module that provides clinically interpretable severity scores and actionable treatment recommendations.
- A scalable and accessible solution for real-time dermatological screening in resource-constrained environments.

II. RELATED WORK

Recent research in dermatological diagnosis has increasingly focused on improving accuracy, robustness, and accessibility through image-based analysis and deep learning techniques. Early approaches primarily relied on manual inspection, where dermatologists visually assess skin lesions using morphological criteria such as the ABCD rule. However, these methods are inherently subjective, time-consuming, and prone to inter-observer variability due to human limitations and the high visual similarity between different skin disease categories [7], [15].

To overcome these limitations, traditional image processing techniques were introduced, where handcrafted features such as colour, texture, and shape descriptors were used for skin disease classification. Although these approaches demonstrated reasonable performance under controlled conditions, they often fail in real-world scenarios due to variations in illumination, skin tone diversity, and complex lesion backgrounds, leading to reduced generalization capability [3], [5].

Subsequently, learning-based approaches were developed to improve classification performance by categorizing lesions as benign or malignant. While these methods improved diagnostic accuracy, they often lack detailed analysis of disease progression, which is crucial for effective clinical decision-making. Region-based lesion detection techniques were also explored to localize affected areas; however, these methods struggle to accurately capture irregular lesion boundaries and spreading patterns, resulting in limited precision in severity estimation [4], [8].

More recently, deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), have significantly advanced the field of skin disease analysis. CNNs enable automatic extraction of discriminative features and have demonstrated strong performance in dermatological image classification tasks [2], [13]. Advanced architectures such as ResNet and MobileNetV2 have further improved efficiency and accuracy, especially in resource-constrained environments [10], [11]. In addition, large-scale datasets such as HAM10000 have played a crucial role in enabling robust model training and evaluation [6], [9].

Despite these advancements, most existing systems primarily focus on disease classification or lesion detection and do not adequately address the integration of input validation and severity-aware analysis. Very few studies combine skin-image verification with quantitative severity estimation, which limits their applicability in real-world clinical decision support systems. Therefore, this work proposes a multi-stage framework that first verifies the presence of human skin using a gatekeeper mechanism and subsequently performs disease classification along with a quantitative severity assessment to improve diagnostic reliability and clinical interpretability.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

III. MATERIALS AND METHODS

The system architecture of the proposed *DermAnalyze AI* is designed to evaluate skin conditions by integrating image classification and severity-aware estimation in a structured workflow. The architecture consists of multiple interconnected modules that handle input acquisition, preprocessing, gatekeeper verification, disease classification, severity score generation, and result interpretation. Each component plays a significant role in ensuring accurate clinical analysis, robustness, and reliable output for end-users in real-world healthcare environments.

The system begins with the user interaction layer, where the user uploads a lesion image through a React.js-based web interface. This dashboard acts as the primary communication medium, enabling clinicians to visualize diagnostic outputs, severity reports, and historical records efficiently. Once the image is uploaded, it is passed to the preprocessing stage. In this stage, the input image is resized to 224×224 pixels and pixel values are normalized to improve model convergence. During training, data augmentation techniques such as rotation, horizontal flipping, zooming, and scaling are applied to improve model generalization under variations in lighting conditions, skin tone diversity, and camera orientation, which is critical for mobile-captured images in real-world scenarios.

After preprocessing, the system performs a *Gatekeeper* verification to determine whether the input image contains human skin. This is achieved using YCbCr colour-space filtering, which effectively separates skin-like regions from the background. In addition, a quality assessment step is incorporated to detect low-quality inputs such as blurred or overexposed images, ensuring improved robustness. If the image is classified as non-skin or of insufficient quality, the system returns an “invalid input” message and halts further processing. This validation mechanism significantly enhances diagnostic integrity, reduces computational overhead, and ensures that only clinically relevant images are analyzed.

The core diagnostic stage involves disease classification using a lightweight MobileNetV2 architecture. This model is selected due to its efficient depth-wise separable convolution design, which enables high feature extraction capability with reduced computational complexity. Transfer learning is employed using pre-trained weights to accelerate convergence and improve classification performance on dermatological datasets. Following classification, the system performs severity estimation by analyzing model confidence scores along with texture and spatial distribution characteristics of the lesion. This hybrid approach improves robustness in severity prediction, especially for irregular lesion boundaries.

To ensure clinical relevance, the system incorporates a Knowledge Base module that maps predicted disease classes and severity levels to standard dermatological guidelines. For instance, a prediction of “Severe Melanoma” triggers an immediate referral alert, while “Mild Nevus” suggests routine monitoring and follow-up. This transformation from probabilistic output to clinical decision support enhances interpretability and usability for healthcare practitioners.

The entire system is implemented using Python as the core programming language, with FastAPI used for backend service deployment and TensorFlow/Keras utilized for model training and inference. The AI engine is trained and validated using the HAM10000 dataset, which contains diverse dermoscopic images representing multiple skin lesion categories, thereby improving model generalization. The system is optimized using appropriate loss functions and adaptive optimisation algorithms such as Adam to enhance convergence stability.

The final output includes the predicted disease label, a severity score, and a visual representation of the lesion region for interpretability. These outputs are displayed through the web interface, providing a consistent and efficient solution for mobile-based dermatological screening. The system demonstrates strong potential for deployment in resource-constrained environments such as rural clinics and telemedicine platforms.

The entire system focuses on balancing high-speed inference with clinical accuracy and interpretability. By automating the workflow from image acquisition to severity-aware diagnosis, the methodology reduces dependency on manual expert intervention while improving accessibility and scalability in healthcare applications.

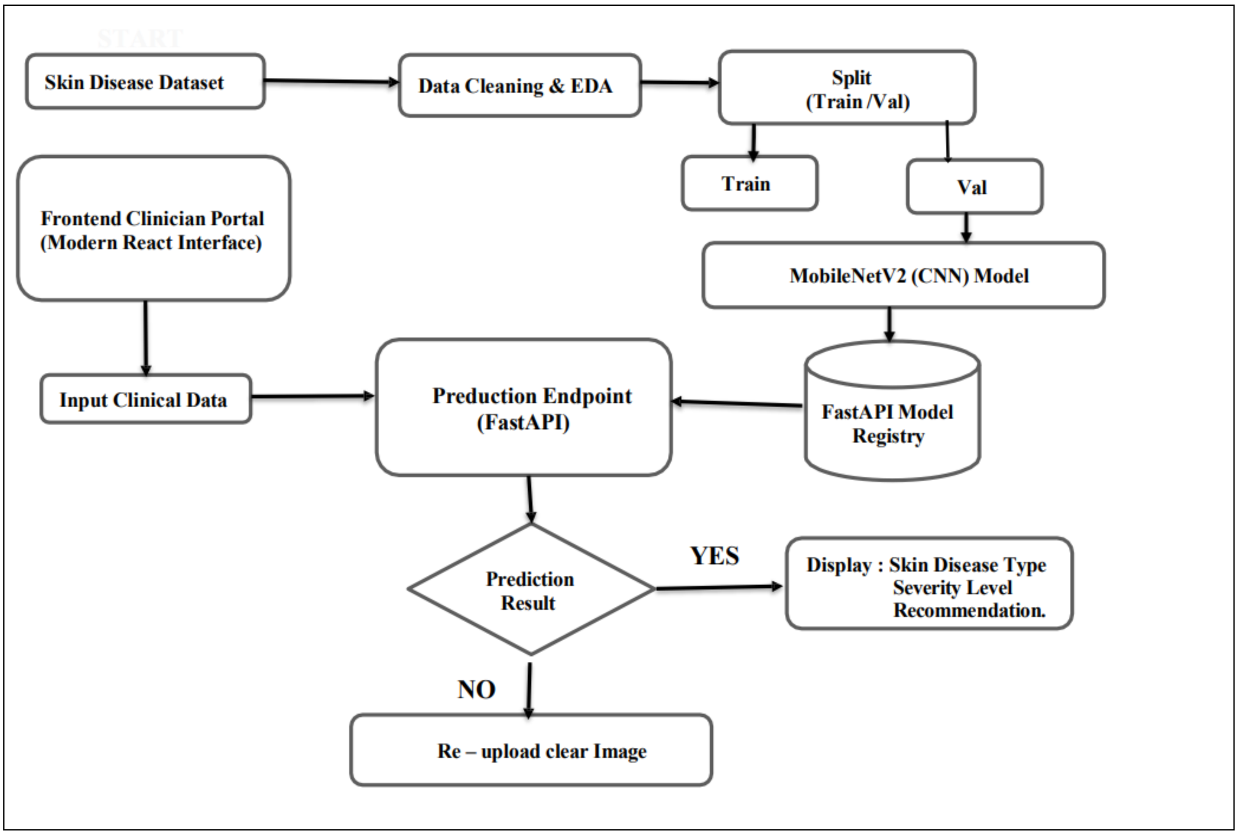

Fig 1. System Architecture for Proposed System

A. Input and Preprocessing Module

The input module allows users to upload images of skin lesions through a React.js-based web interface. Once the image is received, preprocessing is performed to standardize the input for deep learning analysis. The preprocessing steps include resizing the image to a fixed dimension of 224×224 pixels, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, zooming, and scaling during training. These steps improve the robustness of the system and help it handle variations in lighting conditions, skin tones, and camera orientation. As a result, the system becomes more reliable when applied to real-world mobile-captured data. Additionally, batch-wise normalization is applied during training to improve convergence stability.

B. Skin-Tone Gatekeeper Module

In this module, the system verifies whether the input image contains human skin using a combination of YCbCr colour-space filtering and MobileNetV2 with transfer learning. The model uses pre-trained weights for feature extraction and is fine-tuned for the specific task of skin detection and input validation. This approach reduces training time and improves classification accuracy by rejecting non-skin objects. A threshold-based filtering mechanism is also applied to improve robustness under varying illumination conditions. If the input image is identified as human skin, the system proceeds to the next stage. Otherwise, it returns an “invalid input” message and terminates further processing. This ensures that only relevant dermatological images are analyzed, improving overall system efficiency, reliability, and diagnostic integrity.

C. Severity Analysis and Classification Module

For valid skin images, disease classification and severity analysis are performed using an optimized MobileNetV2 architecture. This module performs high-level feature extraction to identify pathological regions of the skin lesion, such as irregular borders, pigmentation changes, and texture variations. The architecture consists of bottleneck blocks that preserve spatial information while reducing computational cost. Depth-wise separable convolutions are used to enhance efficiency while maintaining strong representational power, enabling accurate classification of complex and irregular lesion structures. This detailed analysis enables a more precise evaluation of skin health and disease progression.

D. Severity Score Computation

After identifying the disease and lesion characteristics, the system calculates the level of progression relative to healthy skin standards. Based on this analysis, a numerical severity index is generated. A lower score indicates a mild condition, while a higher score indicates an advanced stage of infection or malignancy. This scoring method provides a clear and interpretable representation of skin health and assists users in understanding the urgency of medical attention required.

The Severity Index is calculated as:

Severity Index (%) = (Detected Lesion Area / Total Analyzed Area) × 100

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

Where:
Detected Lesion Area = pixels classified as pathological
Total Analyzed Area = total pixels of the skin region

Based on this analysis, the system categorises the condition into severity tiers: mild, moderate, and severe. This structured scoring approach enhances clinical interpretability and supports early intervention decisions.

E. Implementation

The proposed DermAnalyze AI system was implemented using standard hardware and modern software tools to ensure efficiency and clinical practicality. The system was developed on a computer with moderate specifications, demonstrating that it can function effectively without requiring high-end computational resources. This makes it suitable for deployment in healthcare environments such as rural clinics, telemedicine platforms, and mobile-based screening applications.

The system was developed using Python as the primary programming language due to its simplicity and strong support for medical imaging and deep learning applications. The development process involved implementing modules for data preprocessing, MobileNetV2-based training, and diagnostic report generation. For backend services, FastAPI was used to enable efficient API communication between the model and user interface.

The core implementation of the diagnostic model was carried out using TensorFlow/Keras, which provides efficient tools for constructing and training deep neural networks. Transfer learning was applied using MobileNetV2 pretrained weights to improve convergence speed and enhance classification accuracy. The model was trained using the HAM10000 dataset, which includes diverse dermoscopic images across multiple skin lesion categories, improving generalization capability.

For optimisation, the Adam optimizer and categorical cross-entropy loss function were used to improve training stability and performance. After training, the system integrates all modules into a unified pipeline, ensuring seamless flow from image input to final diagnostic output.

IV. RESULTS AND DISCUSSION

The proposed *DermAnalyze AI* system was developed and evaluated to assess its effectiveness in identifying skin diseases, detecting lesion patterns, and estimating severity levels. The system demonstrated its ability to process mobile-captured images, verify the presence of human skin through the gatekeeper module, and provide a comprehensive diagnostic output. Unlike traditional systems, the final output of this framework includes the predicted disease name, a categorised severity level, and tailored clinical recommendations based on the pathological condition of the skin.

The system successfully processes dermoscopic input images and generates segmented outputs that clearly highlight pathological regions, enabling effective differentiation between healthy and affected skin areas, as shown in **Fig. 2**.

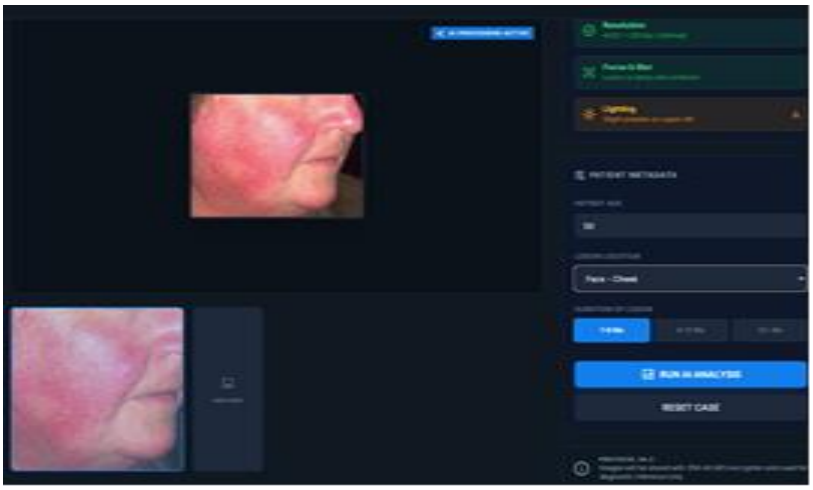

Fig. 2. Input Image and Segmented Output

During testing, the system accurately identified various skin lesions and performed feature analysis to determine the urgency of the condition. For instance, when a lesion was detected, the system not only provided the disease name (e.g., melanoma or nevus) but also assigned a severity level such as mild, moderate, or severe. Based on these findings, the system generated actionable recommendations, such as “routine monitoring” for mild cases or “immediate clinical consultation” for severe cases. The diagnostic output clearly distinguished between healthy skin and pathological regions, enabling improved visual interpretation of the condition.

To evaluate the performance of severity estimation, multiple skin samples were analysed under different lesion conditions. It was observed that lesions with minimal irregularity and smaller affected regions produced lower severity scores, resulting in preventive recommendations. For example, a sample with a uniform lesion area resulted in a “mild” severity classification along with a recommendation for “regular observation.” In contrast, lesions exhibiting irregular borders, higher spread, and increased texture variation resulted in a “severe” classification, accompanied by an urgent recommendation to “consult a dermatologist immediately.” These observations indicate that the system effectively

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

correlates the extent of pathological regions with clinically meaningful severity levels.

Fig. 3. Disease Classification and Severity Display

Figure 3 illustrates the final diagnostic output generated by the proposed *DermAnalyze AI* system, integrating disease classification with severity estimation. The interface displays the predicted skin disease along with the corresponding severity level categorised as mild, moderate, or severe, supported by a quantitative severity score that reflects the extent of the pathological condition. The output also includes a segmented representation of the lesion region, enabling clear differentiation between healthy and affected areas. Based on the predicted disease type and severity level, the system generates clinically relevant recommendations, such as routine monitoring for mild conditions or immediate medical consultation for severe cases. This integrated visual and analytical representation enhances interpretability and supports informed decision-making in dermatological assessment.

Overall, the results demonstrate that the proposed framework provides consistent, accurate, and interpretable outputs, enabling reliable differentiation between disease stages. The integration of image classification, severity estimation, and recommendation generation significantly enhances the practical usability of the system in real-world dermatological screening applications.

V. CONCLUSION AND FUTURE WORK

The proposed *DermAnalyze AI* system presents an effective and reliable approach for evaluating skin health through automated visual analysis. The framework incorporates input validation, disease classification, and severity-aware assessment to generate comprehensive diagnostic outputs, including the identified skin condition, severity level, and clinically relevant recommendations. This integrated approach provides a more objective and consistent evaluation compared to traditional manual inspection methods.

The experimental results demonstrate that the combination of a multi-stage processing pipeline and a lightweight deep learning architecture enables accurate disease identification and reliable severity estimation while maintaining computational efficiency. The inclusion of a gatekeeper mechanism further enhances the robustness of the system by ensuring that only valid dermatological inputs are processed, thereby improving diagnostic integrity.

Despite its effectiveness, the current system can be further extended to enhance its applicability and performance. Future work will focus on incorporating more diverse and large-scale datasets to improve generalisation across different skin types and conditions. In addition, the framework can be expanded to support real-time video-based analysis, enabling continuous monitoring and early detection of dermatological changes. Further improvements may include integration with clinical decision support systems and the incorporation of explainable artificial intelligence techniques to enhance transparency and user trust.

REFERENCES

[1]. D. Makolo, et al., “An optimized deep learning-based system for accurate detection and classification of skin diseases,” International Journal of Research and Innovation in Applied Science (IJRIAS), vol. 10, no. 2, pp. 145–160, 2025.
[2]. P. N. Srinivasu, et al., “Classification of skin disease using deep learning neural networks with MobileNetV2 and LSTM,” Sensors, vol. 21, no. 8, pp. 2852–2870, 2021.
[3]. L. F. Li and H. Wang, “Deep learning in skin disease image recognition: A review,” IEEE Access, vol. 8, pp. 165287–165299, 2020.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26apr1153

[4]. S. Ahmed, et al., "Deep-learning-based super-resolution and classification framework for skin disease detection," Optical and Quantum Electronics, vol. 54, no. 11, pp. 750–765, 2022.
[5]. S. Saiwaeo and N. Phanthumchinda, "Human skin type classification using image processing and deep learning approaches," Heliyon, vol. 9, no. 4, pp. 152–165, 2023.
[6]. P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset: A large collection of multi-source dermatoscopic images," Scientific Data, vol. 5, no. 1, pp. 1–9, 2018.
[7]. A. Esteva, B. Kuprel, R. A. Novoa, et al., "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.
[8]. N. Codella, D. Gutman, M. Celebi, et al., "Skin lesion analysis toward melanoma detection: A challenge at the International Symposium on Biomedical Imaging," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 501–512, 2019.
[9]. M. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset: A large collection of multi-source dermatoscopic images," *Scientific Data*, vol. 5, no. 1, pp. 1–9, 2018.
[10]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.
[11]. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 4510–4520.
[12]. F. Yu, V. Koltun, and T. Funkhouser, "Dilated residual networks," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 472–480.
[13]. G. Litjens, T. Kooi, B. E. Bejnordi, et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.
[14]. H. Nasr-Esfahani, S. Samavi, N. Karimi, et al., "Melanoma detection by analysis of clinical images using convolutional neural network," in *Proc. IEEE Int. Conf. Image Processing (ICIP)*, 2016, pp. 137–141.
[15]. P. Tschandl, C. Rosendahl, and H. Kittler, "Expert-level diagnosis of nonpigmented skin cancer by combined convolutional neural networks," *JAMA Dermatology*, vol. 155, no. 1, pp. 58–65, 2019.
[16]. J. Deng, W. Dong, R. Socher, et al., "ImageNet: A large-scale hierarchical image database," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2009, pp. 248–255.