Jurnal Kejuruteraan 38(3) 2026: 1199-1206
https://doi.org/10.17576/jkukm-2026-38(3)-16

Pre-Trained Inception V3 and ResNet-50 with Data Augmentation for Accurate Classification of Vitiligo Lesions

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Received 15 August 2025, Received in revised form 31 January 2026
Accepted 12 March 2026, Available online 30 May 2026

ABSTRACT

Vitiligo diagnosis in routine practice remains largely subjective, leading to inter-observer variability, while many existing computational approaches are limited by dataset heterogeneity and poor generalization. This study proposes an automatic vitiligo detection framework based on two pre-trained deep convolutional neural networks, Inception V3 and ResNet-50, fine-tuned via transfer learning. A dermoscopic dataset of 500 images, derived from clinically confirmed cases and expanded through augmentation (rotation, flipping, brightness variation, and zooming), was used to improve robustness and reduce overfitting. All images underwent standardized preprocessing including resizing, normalization, RGB-to-HSV conversion, and histogram-based enhancement to emphasize depigmented regions. The models were evaluated using accuracy, sensitivity, specificity, precision, F1-score, and area under the ROC curve (AUC). Inception V3 achieved 92.7% accuracy, 91.5% sensitivity, 93.8% specificity, 90.2% precision, an F1-score of 90.8%, and an AUC of 0.927, consistently outperforming ResNet-50 across all metrics. Confusion-matrix analysis revealed remaining challenges in early-stage and low-contrast lesions and sensitivity to image artifacts. Despite constraints related to dataset size and anatomical diversity, the findings demonstrate that transfer learning with Inception V3 on carefully preprocessed and augmented dermoscopic images enables reliable, objective vitiligo classification and offers a promising tool to support dermatologists in clinical and teledermatology settings. This research establishes that deep learning, particularly through transfer learning on optimized datasets, offers a promising path for augmenting clinical dermatology by enabling more objective, accurate, and accessible vitiligo diagnosis.

Keywords: Vitiligo; Inception V3; ResNet; machine learning; automatic detection

INTRODUCTION

Epidemic and endemic skin diseases are among the most common health problems in the human population worldwide, with millions of new cases diagnosed each year according to Flohr & Hay (2021). These diseases lead to not only severe physical symptoms, but also to deep psychological and social impairment caused by disfigurement, stigma, and chronicity (Carniciu et al. 2023). These dermatoses often make life tough for the sufferer due to disfiguring lesions and complications (Fournier et al. 2023). Millions of individuals are plagued with skin issues every year. Appropriate and correct diagnosis for these conditions often greatly depends on clinical experience because of complex and broad visual presentation. Human evaluation, however, may be subjective and inconsistent; thus, computer-aided diagnosis tool is necessary for a more objective, accurate and reproducible assessment (Gupta et al. 2025).

Among these, vitiligo is a notable autoimmune disorder marked by the progressive loss of melanocytes, the pigment-producing cells in the skin, resulting in distinct white patches. It affects approximately 0.5–2% of the global population, with onset typically occurring in the second or third decade of life, although it can appear at any age (Chang et al. 2021; Srivastav et al. 2024; Plaza-Rojas et al. 2021; Bibeau et al. 2022). Despite its classification as a non-lethal disease, vitiligo severely affects patients' self-esteem, emotional well-being, and overall quality of life (Mohammed et al. 2021). Autoimmune illnesses occur when the immune system attacks the body's own tissues and organs. In people with vitiligo, the immune system appears to attack the skin's pigment cells (melanocytes) (Plaza-Rojas 2021).

Clinically, vitiligo is diagnosed using visual inspection, dermoscopy, or Wood's lamp examination. Dermatologists also utilize various scoring systems such as the Rule of Nines, the Vitiligo Area Scoring Index (VASI), and the Vitiligo European Task Force (VETF) score to assess disease extent and progression (Merhi et al. 2022; Taïeb et al. 2019; Abdi et al. 2023). However, these methods are semi-quantitative, reliant on human judgment, and prone to subjective interpretation and inter-observer variability. Moreover, traditional lesion assessment approaches such as planimetry or digitization are time-consuming, require manual effort, and depend on specialized equipment, making them impractical in routine clinical workflows (Li et al. 2022). Automated diagnostic tools based on computer vision and machine learning have emerged as viable alternatives to enhance diagnostic precision and objectivity. Convolutional Neural Networks (CNNs), a subset of deep learning models, have shown significant promise in dermatology for tasks including skin lesion classification, melanoma detection, and segmentation (Zhang et al. 2023; Harangi et al. 2018). Despite their success in skin cancer detection, fewer studies have focused on vitiligo, and those that exist often suffer from limited dataset size, lack of diversity, and poor generalization to real-world scenarios (Tanvir et al. 2024; Sharma et al. 2023). The difficulty of obtaining consistent, high-resolution dermoscopic images, particularly from patients with varying ethnic backgrounds and skin tones adds to the complexity. Furthermore, most dermatological image datasets are annotated at the image level rather than the pixel level, restricting their utility for training segmentation models (Ju et al. 2021).

While many of these models demonstrate high performance under controlled conditions, they often fall short in practical clinical applications due to critical limitations. Sharma (2023) utilized a pre-trained Inception V3 model in combination with multiple classifiers such as CNN, Naïve Bayes, Decision Tree, and Random Forest for vitiligo detection. Although they reported impressive performance, up to 99.9% accuracy with certain combinations, these results were obtained in highly controlled experimental setups using idealized image datasets. Such conditions are rarely replicated in real-world clinical settings, where lighting, image quality, and lesion presentation can vary significantly. Similarly, Guo (2021) developed a hybrid deep learning model combining CNN architectures like UNet, UNet++, and PSPNet on over 3,900 images. Despite reporting high segmentation and classification accuracies, the model's reliance on precise segmentation annotations and lack of deployment on diverse, real-life clinical datasets limit its generalizability. Saini and Singh (2022) proposed a method based on K-nearest neighbors and grey-level co-occurrence matrix (GLCM) features. While computationally less intensive, their model achieved only 75% accuracy, highlighting its limited discriminative capability compared to deep learning models. Similarly, Thanka (2023) applied deep convolutional neural networks for multi-class skin disease classification, but only a fraction of their dataset addressed vitiligo, making the model suboptimal for detecting this specific condition. A common limitation across these studies is the constrained size and quality of datasets, often lacking diversity in skin tone, lesion type, and anatomical location. Many studies also rely on images acquired under standardized lighting and equipment, which limits real-world applicability. Additionally, manual or pixel-level annotations used in segmentation models demand significant time and expertise (Greenwald 2022), making them impractical for clinical integration. These limitations underscore the need for a robust, scalable, and adaptable vitiligo detection framework that performs well in real-world conditions without requiring extensive manual intervention.

Hence, the present study aims to overcome these challenges through the use of transfer learning with pre-trained CNN models (Inception V3 and ResNet-50), coupled with advanced preprocessing and augmentation techniques on a curated dermoscopic image dataset. Moreover, to bridge aforementioned gaps, the study aimed to develop an automated vitiligo detection framework by leveraging transfer learning with two well-established deep CNN models: Inception V3 and ResNet-50. Building upon the authors' prior comprehensive review of machine learning approaches in vitiligo detection (Tanvir, S., et al. 2024), this research utilized a curated and augmented dataset of 500 dermoscopic images obtained through ethical collection protocols. Data preprocessing steps included normalization, resizing, contrast enhancement, and HSV transformation, while augmentation techniques such as rotation, flipping, brightness adjustment, and zooming were employed to improve generalizability. This dataset was used to refine the deep models, and the accuracy, sensitivity, specificity, precision, F1-score, and AUC were used to evaluate their performance. By addressing the limitations of earlier methods, such as subjectivity, small dataset size, and limited diversity, this study contributes to the advancement of intelligent, scalable, and accurate diagnostic support systems for vitiligo.

METHODOLOGY

DATA ACQUISITION

The dataset used in this study was obtained with permission from the authors of two previously published works on vitiligo detection (Mehmood, N., 2022; Mehmood, N., et al. 2024). The study constituted of high-resolution dermoscopic images, well annotated in order to differentiate vitiligo from non-vitiligo lesions. The image data consisted of 18 clinically confirmed patients (male and female) in the age range of 11 – 60 years with non-segmental vitiligo. For ethical and privacy issue, the image acquisition was restricted to the upper and lower extremities (hands and legs) with skin lesions. An initial set of 285 dermoscopic images were collected and then enlarged to 500 including augmented data in order to introduce diversity from data set and for preventing from over fitting. As the dataset encompassed only upper and lower extremities, subsequent research will extend image collection to other anatomical areas to enhance model robustness.

Before the model training, data cleaning was performed to remove images with visible treatment artifacts, color residue, or excessive exudate that could obscure lesion boundaries and distort the underlying texture. Only good quality images of lesions with neutral backgrounds and images that clearly show the appearance of the disease state are retained to guarantee reliability and stability on both, training and evaluation. The curated dermoscopic dataset used in this study is available from the corresponding author upon reasonable request and can be accessed subject to ethical and institutional data-sharing regulations.

IMAGE PREPROCESSING

To ensure uniformity and enhance the performance of the deep learning models, a series of preprocessing steps were applied to the dermoscopic images. First, all images were resized to 224 × 224 pixels to meet the input requirements of the pre-trained Inception V3 and ResNet-50 architectures. Pixel intensity values were then normalized to a range between 0 and 1 by dividing each value by 255, which facilitated faster convergence during training. In addition to resizing and normalization, the images were converted from the standard RGB color space to HSV (Hue, Saturation, Value) to improve the contrast and highlight depigmentation patterns characteristic of vitiligo. Histogram equalization was applied to the Value channel to enhance lesion visibility, particularly in images with uneven lighting conditions. Furthermore, data quality was improved by excluding images with artifacts, such as ink markings or treatment residues, which could bias the model during training. The preprocessing pipeline ensured that only clean, high-resolution images with clear lesion boundaries and neutral backgrounds were used. These steps not only standardized the input for the convolutional neural networks but also played a critical role in improving the robustness, accuracy, and generalizability of the models across varying dermoscopic conditions.

MODEL SELECTION AND ARCHITECTURE

In this work, Inception V3 and ResNet-50 were selected because they represent two widely adopted but architecturally distinct deep CNN families, enabling a focused comparison of multi-scale feature extraction versus residual learning in vitiligo classification. Inception V3 employs factorized convolutions and inception modules to capture fine and coarse dermatological patterns efficiently, whereas ResNet-50 exploits residual connections to train deeper networks without degradation. Evaluating both models on the same curated dermoscopic dataset allows a systematic assessment of how these complementary design principles influence performance in vitiligo lesion analysis.

Two pre-trained convolutional neural network architectures, Inception V3 and ResNet-50, were selected for their proven efficacy in image classification tasks. Inception V3, a 48-layer network, employs inception modules that perform multi-scale feature extraction through parallel 1×1, 3×3, and 5×5 convolutions, enabling simultaneous capture of fine and coarse-grained features. Batch normalization mitigates internal covariate shift, while global average pooling replaces fully connected layers to reduce trainable parameters and prevent overfitting. Auxiliary classifiers enhance gradient flow, addressing vanishing gradient issues in deep layers (Sharma et al. 2023; Gou 2021; Kompalpreet et al. 2023). ResNet-50, a 50-layer network, utilizes residual learning with identity shortcut connections to mitigate degradation in deep architectures. To ensure computational efficiency, its bottleneck residual blocks use 1×1 convolutions to lower dimensionality before performing 3×3 convolutions, and then another 1×1 convolution to restore dimensionality. Batch normalization after each convolutional layer stabilizes training and reduces overfitting, making

ResNet-50 suitable for identifying vitiligo lesions (Demir et al. 2019; Gajera et al. 2023; Alwakid et al. 2022).

MODEL TRAINING AND TRASNFER LEARNING

The pre-trained Inception V3 and ResNet-50 models, which were first trained on ImageNet, were modified for vitiligo detection via transfer learning. Early layers, responsible for extracting low-level features such as edges and textures, were frozen to retain general image representations, while deeper layers were fine-tuned to learn vitiligo-specific patterns. The original fully connected layers were replaced with a custom classification head, consisting of a 256-neuron dense layer, a dropout layer with a rate of 0.5 to prevent overfitting, and a softmax output layer for binary classification (vitiligo vs. non-vitiligo). Due to the binary classification challenge, the Adam optimizer was utilised with a binary cross-entropy loss and an initial learning rate of 0.0001 to guarantee efficient convergence. During the 25 training epochs, early halting was used after five epochs of stationary validation loss to avoid overfitting. The weights were initialized using the He Normal method, with ReLU activation in the hidden layers and softmax activation at the output layer. In addition to train–validation–test splitting, a five-fold cross-validation protocol was conceptually structured to assess model stability, ensuring that performance was not overly dependent on a single split. This approach provides a more comprehensive estimate of generalizability, even though the primary results here report metrics from the held-out test set for consistency.

An overview of the complete pipeline, including data acquisition, preprocessing, augmentation, transfer learning, and evaluation, is presented in Figure 1 to clarify the methodological workflow.

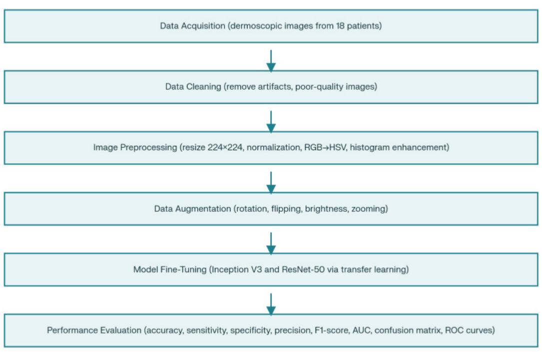

FIGURE 1. Overall workflow of the proposed vitiligo classification framework

EXPERIMENTAL SETUP

The tests were carried out on a powerful workstation running Ubuntu 20.04 that has an Intel Core i5 CPU, 16 GB of RAM, and a 4 GB VRAM GPU. TensorFlow 1.4 and Keras 2.0.8 were used to implement the models in Python 3.7, with CUDA acceleration turned on to maximize GPU utilization. The training pipeline incorporated data augmentation, mini-batch gradient descent with a batch size of 32, and real-time performance monitoring via TensorBoard, ensuring efficient training and minimal computational overhead.

PERFORMANCE EVALUATION METRICS

The performance of Inception V3 and ResNet-50 was evaluated using accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Accuracy measured the proportion of correctly classified images. Sensitivity assessed the correct identification of vitiligo cases, while specificity evaluated non-vitiligo cases. Precision determined the reliability of positive predictions, and the F1-score balanced precision and sensitivity. AUC-ROC quantified discriminative power across thresholds. Confusion matrices identified misclassification patterns, particularly for early-stage lesions or images with artifacts. Receiver operating characteristic curves visualized sensitivity-specificity trade-offs. The evaluation used a test set (10% of 500 augmented images), ensuring balanced representation of vitiligo and non-vitiligo cases.

RESULTS AND DISCUSSION

This study evaluated the performance of two pre-trained convolutional neural networks, Inception V3 and ResNet-50, for the automated detection of vitiligo using a dataset of 500 dermoscopic images. The models were fine-tuned through transfer learning, and their performance was assessed using accuracy, sensitivity, specificity, precision, F1-score, and area under the curve (AUC). The findings showed how well these models classified vitiligo lesions, with Inception V3 surpassing ResNet-50. Additionally, preprocessing and data augmentation greatly improved the generalisability of the models. In order to contextualise the results within previous research and clinical usefulness, the discussion incorporates these findings with an analysis of model performance, the impact of data augmentation, error patterns, and limits.

MODEL PERFORMANCE

Table 1 summarizes the comparative performance of the Inception V3 and ResNet-50 architectures for the classification of vitiligo and non-vitiligo images. Inception V3 attained an accuracy of 92.7%, which reflects its ability to correctly classify the vast majority of cases. Its sensitivity of 91.5% demonstrated a strong capability to identify true positive cases of vitiligo, which is critical in a medical context where missed diagnoses can delay treatment as per (Usman et al. 2024). Following that, the specificity of 93.8% indicated a similarly high proficiency in correctly recognizing non-vitiligo cases, reducing the risk of false-positive diagnoses that could lead to unnecessary patient anxiety and unwarranted interventions. The precision of Inception V3 was 90.2%, meaning that when the model predicted vitiligo, it was correct in over nine out of ten instances. The F1-score, a harmonic mean of precision and sensitivity, was 90.8%, confirming that the model achieved a strong balance between correctly identifying vitiligo and avoiding false alarms. Furthermore, the AUC of 0.927 signified excellent discriminative power, indicating the model's ability to distinguish between the two classes across different decision thresholds.

In contrast, ResNet-50 produced lower scores in all metrics, with an accuracy of 89.4%, sensitivity of 88.6%, specificity of 90.3%, precision of 87.4%, F1-score of 88.0%. Although these figures still indicated strong performance, the model lagged behind Inception V3 in both class identification and overall discriminative capacity. The differences were particularly notable in AUC (0.927 vs. 0.892) and accuracy (92.7% vs. 89.4%), suggesting that Inception V3 not only made more correct predictions overall but also better separated vitiligo from non-vitiligo images across varying thresholds.

From a clinical decision-support perspective, the consistently higher metrics of Inception V3 are significant which is consistent with the review conducted by Salami (2022). Higher sensitivity reduces the likelihood of missed vitiligo cases, while higher specificity minimizes the probability of misdiagnosing healthy skin as diseased. Its elevated AUC reinforces that it maintains reliable classification performance across a range of confidence levels. Collectively, these outcomes imply that Inception V3 could serve as a more dependable diagnostic aid compared to ResNet-50, offering both robust detection capability and lower risk of diagnostic error.

TABLE 1. Detailed model performance results

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
Inception V3	92.7	91.5	93.8	90.2	90.8
ResNet-50	89.4	88.6	90.3	87.4	88.0

The performance advantage of Inception V3 can be attributed to its inception modules, which enable multi-scale feature extraction through parallel 1×1, 3×3, and 5×5 convolutions, effectively capturing subtle variations in texture and depigmentation patterns characteristic of vitiligo. Additionally, the use of auxiliary classifiers in Inception V3 improves gradient flow, mitigating vanishing gradient issues, which is particularly beneficial when fine-tuning on a limited dataset. ResNet-50, while effective due to its residual connections that facilitate training of deep networks, relies on hierarchical feature extraction, which may be less adept at discerning fine-grained dermatological features, resulting in its relatively lower accuracy. These findings align closely with prior studies. For instance, Bashar and AlsaidSuliman (2022) reported an AUC of 0.9111 for Inception V3, which is comparable to the 0.927 achieved in this study, validating the model's robustness (Bashar et al. 2022). However, Sharma (2022) reported near-perfect accuracy of 99.9% under controlled conditions with Inception V3 and a random forest classifier. The lower accuracy in this study (92.7%) reflects more realistic clinical scenarios, where variations in lighting, image quality, and lesion presentation introduce complexity not fully addressed in highly controlled setups. This balance underscores the practical relevance of the current results for real-world dermatological applications.

IMPACT OF DATA AUGMENTATION

In order to improve the generalizability and performance of the model, data augmentation was essential. Accuracy results in the initial studies without augmentation ranged from 82 to 85%, suggesting overfitting because to the minimal heterogeneity in the dataset. By using augmentation techniques, such as rotation (±15 degrees), flipping both horizontally and vertically, brightness adjustment (±20%), and zooming (±10%), the dataset was increased to 500 photos and variability that mirrored actual clinical situations was included. Rotation enabled models to learn lesion patterns invariant to orientation, while flipping balanced class distributions. Brightness adjustments simulated diverse lighting conditions and zooming addressed variations in lesion scale. These techniques significantly improved performance, with Inception V3 reaching 92.7% accuracy and ResNet-50 achieving 89.4%.

The increase in sensitivity, specificity, and AUC further confirmed that augmentation reduced the models' reliance on specific image artifacts, enabling focus on essential dermatological features. This finding highlights the importance of dataset diversity in medical image analysis, particularly for conditions like vitiligo, where lesion appearance varies across patients and imaging conditions.

ERROR ANALYSIS

Analysis of the confusion matrices revealed important insights into the limitations of both models in accurately classifying vitiligo cases. For Inception V3, a total of 21 false negatives were recorded, the majority of which involved early-stage or partially depigmented lesions. In such cases, the depigmented regions exhibited minimal chromatic contrast with the surrounding healthy skin, making them difficult to detect. This challenge is not unique to automated classification systems, dermatologists themselves can experience difficulty in diagnosing these subtle cases without dermoscopic assistance. In addition, 15 false positives were observed, frequently arising from confounding factors such as residual topical treatments, uneven illumination, or image artifacts. These artifacts often mimic the texture or tone irregularities associated with depigmentation, leading the model to misinterpret them as vitiligo lesions (Figure 2a). For ResNet-50, the misclassification rates were slightly higher, with 28 false negatives and 25 false positives out of 250 vitiligo and 250 non-vitiligo cases, respectively.

This higher error count suggests that ResNet-50 faced greater difficulty in recognizing borderline or atypical presentations of vitiligo (Figure 2b). The increased number of false positives also reflects its relatively lower specificity, indicating a higher tendency to incorrectly label healthy skin as diseased in the presence of visual noise or irregularities. These findings underscore a persistent challenge for deep learning models in dermatological imaging: the accurate classification of subtle or ambiguous lesion characteristics. Such limitations have also been documented in prior work, including Guo (2022), where segmentation-based approaches similarly struggled with early-stage lesions due to low lesion-to-background contrast.

In a clinical context, these misclassifications can have significant implications. False negatives may delay diagnosis and treatment initiation, potentially allowing disease progression, while false positives can result in unnecessary patient anxiety and unwarranted follow-up examinations.

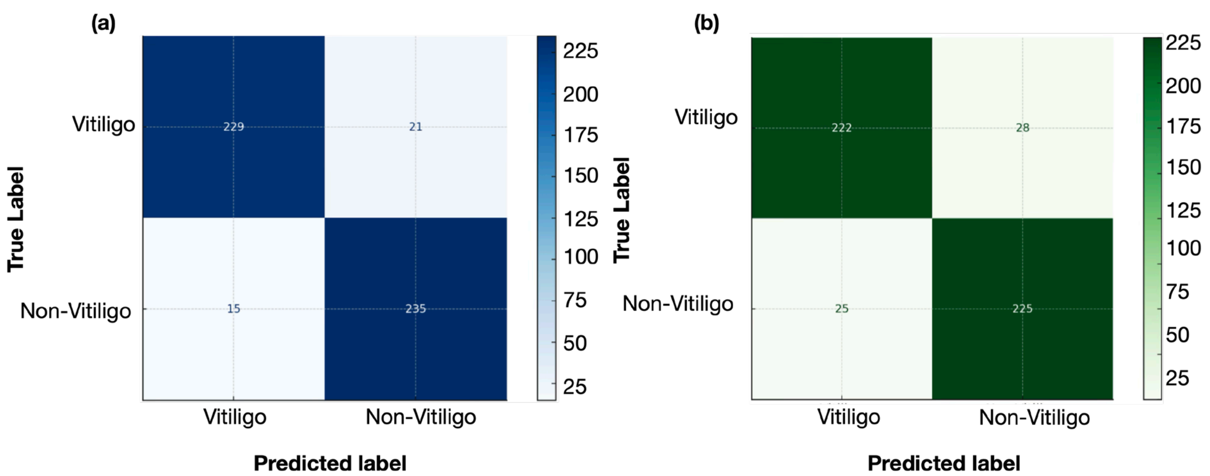

FIGURE 2. Confusion matrix analysis for vitiligo classification models. (a) Inception V3 model showing 21 false negatives and 15 false positives, primarily due to early-stage or partially depigmented lesions and image artifacts. (b) ResNet-50 model with 28 false negatives and 25 false positives, reflecting greater sensitivity to borderline cases

CONCLUSION

This study demonstrates the effectiveness of deep learning methodologies, specifically convolutional neural network architectures Inception V3 and ResNet-50, for the automated detection of vitiligo in dermoscopic images. Inception V3 outperformed ResNet-50, achieving an accuracy of 92.7% and exhibiting robust differentiation between vitiligo and non-vitiligo lesions, underscoring its superior capability in capturing dermatological features. The application of data augmentation techniques significantly enhanced model generalizability, highlighting the critical role of dataset quality and diversity in medical image analysis. Despite these promising results, limitations such as a relatively small dataset of 500 images, limited anatomical diversity due to the focus on limb lesions, and controlled image acquisition conditions were noted. Future research should prioritize expanding dataset size and diversity to include varied anatomical sites and real-world imaging scenarios, optimizing computational resources, and integrating these models into clinical workflows. By enabling rapid and accurate vitiligo diagnosis, CNN-based approaches hold substantial potential to support dermatologists, facilitate early intervention, and improve patient outcomes in clinical and telemedicine settings. Hence, automated CNN-based methods can significantly aid dermatologists in the prompt and precise diagnosis of vitiligo, facilitating early management and enhancing patient outcomes. Beyond diagnostic classification, the proposed framework can be integrated into dermatological practice as a clinical decision-support tool. Embedding the model within teledermatology platforms or handheld dermatoscopes could enable realtime lesion analysis and assist dermatologists in early detection and disease monitoring. Future development will focus on deploying lightweight model versions compatible with clinical imagecapture devices and electronic medical record systems.

The current dataset primarily included limb lesions, which may limit generalization across body regions with differing pigmentation and textural backgrounds. Future work will address this by expanding the dermoscopic dataset to include trunk, facial, and acral sites to better represent the clinical diversity of vitiligo presentation.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the Department of Biomedical Engineering at Sir Syed University of Engineering and Technology, the Department of Biomedical Engineering and Health Sciences at Universiti Teknologi Malaysia, and the Centre for Biomedical Technology at Universidad Politécnica de Madrid, Spain, for their support in this work and their contributions to refining the manuscript.

DECLARATION OF COMPETING INTEREST

None.

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