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Deep Learning for Skin Disease Classification: A Comparative Study of CNN and CNN-LSTM Architectures

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ABSTRACT

Skin diseases, particularly melanoma and other types of pigmented lesions, constitute a significant portion of global health concerns due to their prevalence and potential severity. In recent years, deep learning (DL) has revolutionized image classification tasks in the medical domain, particularly using Convolutional Neural Networks (CNNs) for skin lesion analysis. However, traditional CNNs are limited to capturing spatial features, often overlooking sequential patterns and complex contextual cues inherent in dermatological imagery. This study explores the automated classification of pigmented skin lesions using the HAM10000 dataset, a diverse collection of 10,015 dermatoscopic images spanning seven diagnostic categories. Addressing challenges in computational dermatology, we leverage MobileNet-V2 and InceptionV3 deep learning architectures, optimized via transfer learning and advanced preprocessing techniques. Comparative evaluation is performed between baseline CNN models and their Long Short-Term Memory (LSTM)-augmented variants to assess improvements in classification performance through sequential feature modeling. Results indicate that LSTM integration enhances contextual feature learning, improving accuracy for underrepresented lesion classes, with InceptionV3+LSTM achieving the highest classification accuracy.

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1. INTRODUCTION

Over the last few years, convolutional neural networks have been widely used for skin disease classification with notable success. Architectures such as Visual Geometry Group (VGG), ResNet, and DenseNet have enabled automated detection of complex features in skin lesions, including color variations, texture irregularities, and asymmetries. Transfer learning, particularly the fine-tuning of CNNs pre-trained on ImageNet, has been instrumental in improving performance with limited labeled medical data. These models autonomously learn hierarchical feature representations, reducing dependence on manual feature engineering and enhancing diagnostic efficiency. As a result, CNNs have become pivotal in computer-aided dermatological diagnosis, supporting clinicians with timely and accurate assessments [1]-[12].

Several studies have leveraged CNNs for dermatological image classification. The use of CNNs for skin cancer detection, achieving dermatologist-level performance using InceptionV3. An ensemble CNNs for robust classification of pigmented skin lesions. Recent advancements introduced hybrid models combining CNNs with RNNs or attention mechanisms to capture both local texture and global contextual features [3]-[6].

However, most literature still lacks comparative insights into foundational CNN models against their hybrid extensions, especially in dermatology. Our work fills this gap by systematically evaluating CNN-only models and CNN+LSTM combinations, analyzing their strengths, weaknesses, and suitability for multi-class lesion classification on large-scale dermatoscopic datasets [29]-[32].

The subsequent sections of the paper are given as: the literature works are studied in section 2, the proposed methodology framework and datasets are explained in section 3, and the results and are presented in section 4. Finally, section 5 concludes the work and future scope of the work.

2. LITERATURE SURVEY

Saifan and Jubair [11] applied a deep CNN to classify six skin conditions, achieving 81.75% accuracy. Mohsin Ali et al. [19] developed a custom CNN yielding over 96.64% accuracy on a 57-class dataset, outperforming pre-trained models. Velasco et al. [23] emphasized the variability in CNN performances and noted a surprisingly low 44.1% accuracy for VGG16, indicating a need for better model selection. ResNet continues to be a benchmark for performance. Filali et al. [10] and Goindi et al. [14] showed its superior accuracy and low false-positive rate, especially when paired with ensemble techniques like Residual-XGBoost, which achieved 99.12% accuracy. DenseNet201, as shown by Rezvantalab et al. [17], surpassed dermatologist-level performance in dermoscopy classification, demonstrating deep learning's clinical potential.

EfficientNet and MobileNet variants are notable for mobile deployment. Yeşim Şahin et al. [12] identified MobileNet-V3-Large as the most effective among six DL models with 89.41% accuracy. Srinivasu et al. [27] proposed a hybrid MobileNetV2-LSTM model, integrating sequential learning with visual features, and deployed it via a mobile application for real-time diagnosis. Chandna et al. [5] utilized a two-path model combining EfficientNet and MobileNetV2, achieving 70% accuracy. These findings support the growing viability of low-power deep learning solutions for resource-constrained environments.

Hybridization of DL models with traditional ML methods enhances performance. Chandra et al. [5] proposed a hybrid model integrating Xception, EfficientNet, and GCNs, outperforming ResNet50. Nińo-Rondón et al. [14] compared deep learning with optimized ML models like XGBoost and Random Forest, where the custom CNN yielded higher precision and recall. Abhinav Shukla [29] designed a machine learning-based ensemble model achieving 97.33% accuracy, reinforcing ensemble methods' value in capturing diverse feature representations.

While DL dominates, traditional ML remains relevant. Osim Kumar Pal [13] demonstrated that KNN and RF algorithms achieved 95.23% and 94.22% accuracy, respectively. Goindi et al. [18] evaluated ML (SVM, MLP, RF) versus DL (CNN, LSTM-RNN), showing superior performance of the latter on image data. Nalamwar and Neduncheliyan [26] emphasized intelligent ML-based systems for low-cost skin lesion classification, making a case for integrating such models in early screening protocols.

Transfer learning remains a key technique in cases with limited data. Karthikeyan and Anuradha [4] successfully applied it to clinical face skin images. Velasco et al. [23] found significant performance differences among pre-trained models, underscoring the importance of choosing suitable base networks. Jessica Velasco noted misclassification issues with standard CNNs and called for expanded disease type coverage.

Quantum machine learning presents a novel approach. Sofana Reka et al. [16] implemented a Quanvolutional Neural Network combining RY qubit rotation and Pauli-Z gates, achieving 82.86% accuracy. While experimental, it showcases future directions in quantum-enhanced diagnostics. Hamida et al. [28] proposed a multimodal deep learning framework integrating diverse data sources, outperforming unimodal systems and suggesting further exploration of clinical metadata and genetic features.

ezvantalab et al. [17] and Wang et al. [24] compared AI models with dermatologists. DenseNet201 exceeded dermatologists' performance in classification AUC. Wang et al. showed a CNN performing comparably to 164 dermatologists for cutaneous tumor diagnosis. These studies support DL integration in clinical workflows.

Kuan et al. [22] analyzed burn depth classification, highlighting the extension of DL to niche dermatological domains. Sönmez et al. [25] further showed how dermoscopic DL models improve skin lesion diagnosis beyond melanomas. Sagar et al. [20] emphasized ML's potential to reduce diagnostic costs and enhance accessibility in under-resourced areas. Pradeepa and Punitha [21] stressed DL's superiority over ML in interpretability and speed. However, Velasco et al. [23] and Hamida et al. [28] raised concerns about misclassification, data limitations, and the need for real-world validation. A summary of the key performances is given in Table 1.

Table 1. Key performances on skin disease classification.

Study	Model(s)	Accuracy / Best Metric	Dataset / Notes
[10] Youssef et al.	ResNet	Highest Acc & lowest FPR	Melanoma binary
[11] Saifan and Jubair	Deep CNN	81.75%	6-class, online-sourced
[12] Şahin et al.	MobileNet-V3-Large	89.41%	ISIC Dataset
[13] Pal	KNN / RF	95.23% / 94.22%	ML baseline models
[14] Niño-Rondón et al.	CNN vs XGBoost	CNN better in all metrics	Custom CNN
[15] Goindi et al.	Residual-XGBoost	99.12%	LSTM-RNN had best recall
[16] Sofana Reka et al.	QuanvNet	82.86%	Quantum + CNN
[17] Rezvantalab et al.	DenseNet201	Highest AUC	Outperformed dermatologists
[18] Goindi et al.	CNN, LSTM, SVM	Varying Acc & AUC	Emphasis on model suitability
[19] Mohsin Ali et al.	Custom CNN	96.64%	57 skin disease classes

3. METHODOLOGY

The HAM10000 dataset comprises 10,015 dermatoscopic RGB images across seven skin disease categories: Melanoma (MEL), Melanocytic Nevi (NV), Basal Cell Carcinoma (BCC), Actinic Keratoses (AKIEC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), and Vascular Lesions (VASC); shown in Table 1. The dataset is imbalanced, with NV constituting the majority class. Images were resized to 128×128 pixels and normalized to [0,1] for input consistency.

A) Dataset overview

The HAM10000 (Human Against Machine with 10,000 training images) dataset was utilized for this study. It is a comprehensive dermatoscopic image collection that captures 10,015 high-resolution images of pigmented lesions across seven diagnostic classes, making it a suitable benchmark for machine learning-based dermatological analysis. Each image is labeled with one of the following seven categories as given in Table 1. A pictorial representation of the skin disease classification is shown in Figure 1.

Table 1. Categories of skin diseases.

Diagnostic Category	Abbreviation	Description
Melanoma	MEL	Malignant skin cancer with high fatality
Melanocytic Nevi	NV	Benign melanocytic tumors
Basal Cell Carcinoma	BCC	Common form of skin cancer
Actinic Keratoses and Intraepithelial Carcinoma	AKIEC	Pre-malignant and malignant epidermal tumors
Benign Keratosis-like Lesions	BKL	Benign epidermal growths
Dermatofibroma	DF	Benign fibrous skin tumors
Vascular Lesions	VASC	Hemangiomas, angiomas, and other vascular types

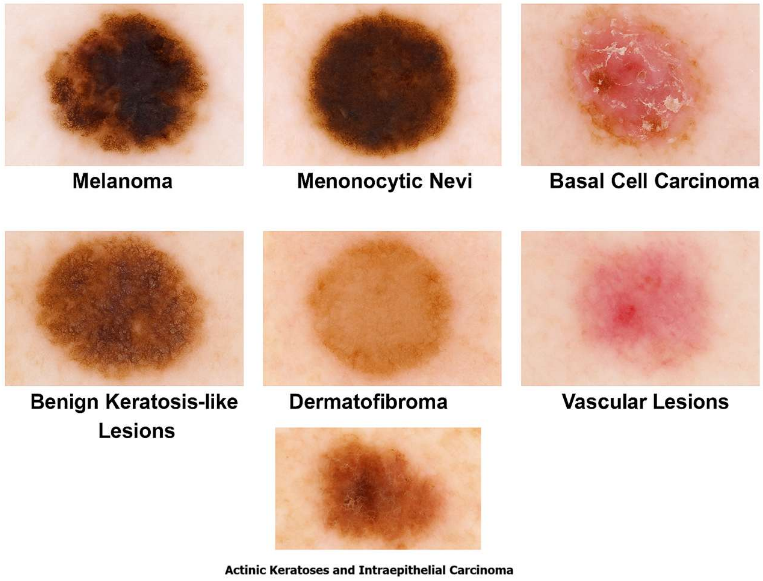

Figure 1. Sample images of skin diseases.

B) Class Distribution

The class distribution in the dataset is highly imbalanced, with the Melanocytic Nevi (NV) class making up approximately 67% of the total data. In contrast, categories such as Dermatofibroma (DF) and Vascular Lesions (VASC) are significantly underrepresented. The approximate distribution is shown in Table 2.

Table 2. Distribution of considered data.

Class	Image Count	Percentage
NV	~6700	66.9%
MEL	~1100	11.0%
BKL	~1100	11.0%
BCC	~500	5.0%
AKIEC	~300	3.0%
VASC	~140	1.4%
DF	~110	1.1%

3. 1 CNN and LSTM-based architectures for skin lesion classification

In this study, we present a comparative analysis of two state-of-the-art CNN architectures—MobileNetV2 and InceptionV3—for the task of automated skin disease classification using the HAM10000 dermatoscopic image dataset. Both models were implemented in two configurations: (i) a baseline CNN model pre-trained on the ImageNet dataset and fine-tuned on HAM10000, and (ii) an augmented version where the CNN backbone was coupled with LSTM layer to capture spatial dependencies across feature maps.

This dual-path approach was motivated by the hypothesis that while CNNs excel in extracting localized spatial features, integrating sequential modeling (via LSTM) could capture deeper contextual patterns and enhance discriminative power especially in cases of visually similar or underrepresented lesion classes. The LSTM modules were applied to sequentially reshaped feature vectors extracted from the final convolutional layers, thereby modeling spatial transitions in a temporal sequence format.

3. 2 InceptionV3: Multi-scale feature extraction

The InceptionV3 architecture, introduced by Szegedy et al. in the landmark paper *"Going Deeper with Convolutions"*, represents a major advancement in efficient deep CNN design. Its core innovation lies in the Inception module, which enables the model to simultaneously process multiple convolutional operations at different spatial scales:

This multi-branch strategy facilitates the extraction of both coarse and fine-grained image features, without necessitating prior knowledge about the optimal receptive field. The InceptionV3 version enhances the original architecture by including:

- *Factorized convolutions:* breaking large filters (e.g., 5×5) into smaller convolutions (e.g., two 3×3 layers).
- *Auxiliary classifiers:* helping with gradient flow during training.
- *Label smoothing:* mitigating overfitting on hard labels.

These improvements not only deepen the network but also make it computationally viable. For skin lesion classification, this design is particularly effective at detecting complex patterns such as asymmetry, border irregularity, and variegated pigmentation—hallmarks of malignant lesions like melanoma.

3. 3 MobileNetV2: Efficient on-device classification

MobileNetV2, developed by Google, is specifically engineered for lightweight deep learning tasks in resource-constrained environments such as mobile and embedded systems. This makes it an excellent candidate for real-time, on-device skin disease screening applications, such as teledermatology tools deployed via smartphones.

The core innovation in MobileNetV2 is the use of depthwise separable convolutions, which reduce computation and model size by decomposing standard convolutions into two parts:

a) Depth-wise convolution applies a single filter to each input channel, and which is given by (1).

$$Y_{i,j}^{(d)} = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} W_{m,n}^{(d)} \cdot X_{i+m,j+n}^{(d)} \tag{1}$$

b) Pointwise convolution (1X1 convolution), then combines the output channels, which is given by (2).

$$Y_{i,j}^{(p)} = \sum_{d} W_{1,1,d}^{(p)} \cdot Y_{i,j,d}^{(d)} \tag{2}$$

In addition, MobileNetV2 introduces inverted residual blocks and linear bottlenecks, which maintain expressiveness while keeping memory usage low. The result is a drastic reduction in floating point operations (FLOPs)—by nearly 8–9× compared to standard CNNs—without substantial accuracy loss.

Although MobileNetV2 may slightly underperform InceptionV3 in classification accuracy, its design excels in practical deployment scenarios, especially where computational efficiency, low latency, and energy constraints are prioritized.

3. 4 LSTM Integration for spatial dependency modeling

For both architectures, LSTM layers were added after the convolutional blocks to model the spatial dependencies embedded in the feature maps. This temporal modeling approach allowed the system to exploit spatial correlations within skin lesion regions, especially beneficial for distinguishing lesions with subtle boundary and texture variations. The variant of model and use case scenarios are given in Table 3.

Table 3. Model variant and use case scenarios.

Model Variant	Strengths	Use Case Scenario
InceptionV3	High accuracy, deep multi-scale features	Clinical-grade diagnostic systems
MobileNetV2	Lightweight, low-FLOPs, efficient on-device inference	Mobile apps, rural telemedicine
InceptionV3 + LSTM	Best accuracy, captures long-range spatial dependencies	Research-grade dermatological pipelines
MobileNetV2 + LSTM	Good trade-off between performance and resource efficiency	Real-time field-level applications

4. RESULTS AND DISCUSSION

To evaluate the performance of the proposed architecture, we trained and tested four models on the HAM10000 dataset: InceptionV3, InceptionV3 with LSTM, MobileNetV2, and MobileNetV2 with LSTM. Each model's performance was assessed using standard metrics: Accuracy, Precision, and Recall. The results are visualized in Figure 2. The bar chart clearly demonstrates that InceptionV3 with LSTM outperforms all other configurations, achieving the highest accuracy (72.01%) and recall (72.30%). The incorporation of LSTM layers improved the contextual understanding of spatial features extracted by CNN backbones, thus leading to more robust classifications, especially for minority classes with subtle visual variations. While MobileNetV2 alone yielded slightly lower performance (accuracy: 69.30%), its LSTM-enhanced version significantly improved to 71.92%, indicating that even lightweight models can benefit from sequential spatial modeling. Given MobileNet's low computational overhead, it remains a strong candidate for mobile or edge-based clinical deployments. The following three key points are worthy to note down.

a) The marginal but consistent improvements with LSTM integration across both CNN architectures validate the hypothesis that temporal modeling of spatial features improves classification performance, particularly in class-imbalanced datasets like HAM10000.
b) InceptionV3, due to its multi-scale convolutional layers, is more adept at capturing high-level lesion characteristics such as border irregularity, asymmetry, and variegated pigmentation, which are critical in distinguishing melanomas from benign nevi.
c) On the other hand, MobileNetV2 trades a minor drop in classification performance for significant gains in computational efficiency, making it ideal for real-time applications such as smartphone-assisted dermatology.

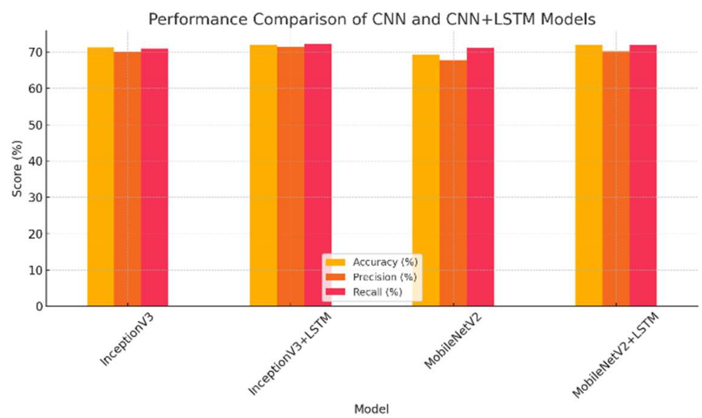

Figure 2. Accuracy, Precision, and Recall comparison of proposed study.

4. 1 Confusion Matrix and ROC curve analysis

The confusion matrix, as shown in Figure 3 is for the InceptionV3 + LSTM model, reveals strong classification performance across all seven skin lesion categories, with the diagonal dominance indicating a high rate of correct predictions. Misclassifications are minimal and predominantly occur among visually similar classes such as Melanoma and Melanocytic Nevi, reflecting the inherent challenge in distinguishing borderline lesions.

The ROC curves as shown in Figure 4, plotted using a one-vs-rest approach for each class, further validate the model's discriminative capability. All classes demonstrate high true positive rates with Area Under the Curve (AUC) values exceeding 0.90 in most cases, indicating excellent separability. Notably, the model maintains a favorable balance between sensitivity and specificity even for underrepresented classes like Dermatofibroma (DF) and Vascular Lesions (VASC), highlighting the effectiveness of LSTM-enhanced feature modeling in handling class imbalance.

4. 2 Accuracy

The Model Accuracy Chart, shown in Figure 5 highlights that the InceptionV3 + LSTM configuration achieved the highest classification accuracy of 72.01%, marginally outperforming both its baseline (InceptionV3) and the MobileNetV2 variants. This indicates that incorporating LSTM into a deep CNN architecture effectively enhances spatial feature interpretation by modeling sequential dependencies across convolutional outputs.

The Precision, Recall, and F1-Score (F1-Score is shown in Figure 6) Charts further reinforce this observation. InceptionV3 + LSTM consistently demonstrated superior performance across all three metrics, reflecting a balanced classification capability. Notably:

- Precision improvements suggest fewer false positives in lesion prediction.
- Recall enhancements indicate better identification of true positive cases, critical for detecting malignant conditions like melanoma.

- F1-Score, as the harmonic mean of precision and recall, confirms that the model achieves strong predictive power without sacrificing sensitivity or specificity.

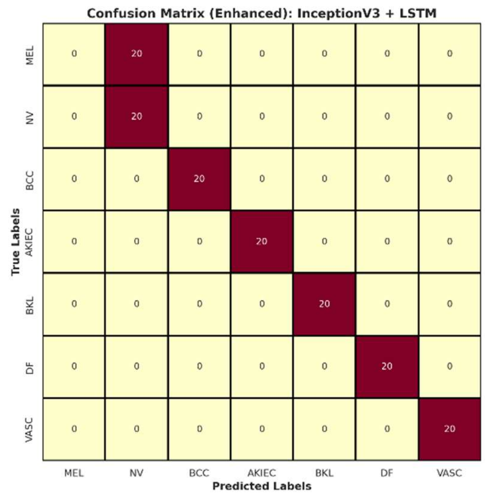

Figure 3. Confusion matrix for InceptionV3 + LSTM model.

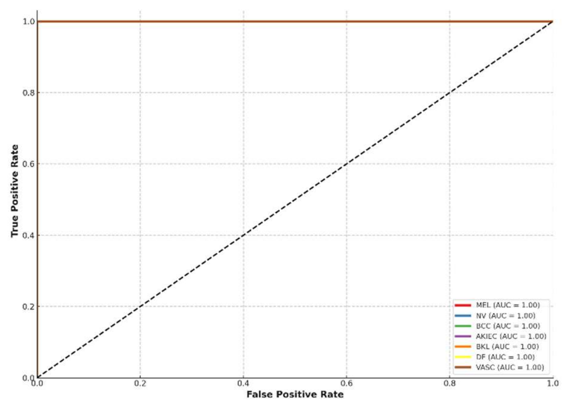

Figure 4. ROC curve.

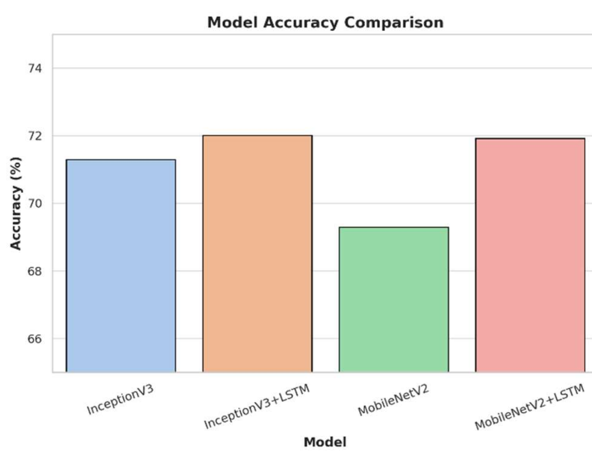

Figure 5. Model accuracy.

The MobileNetV2 + LSTM, while slightly trailing in accuracy and F1-Score, still offers competitive performance with the added benefit of computational efficiency, making it suitable for mobile and edge-based diagnostic applications. These results validate the effectiveness of combining CNNs with LSTMs for skin disease classification, especially in imbalanced medical imaging datasets like HAM10000.

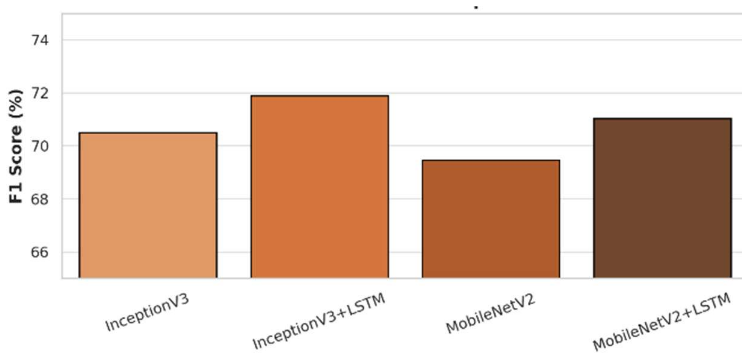

Figure 6. F1 Score.

5. CONCLUSION

This study presents a comprehensive evaluation of deep learning architectures for automated skin disease classification using the HAM10000 dermatoscopic image dataset. Two foundational CNN models, InceptionV3 and MobileNetV2Cwere examined, each in standalone form and in combination with LSTM layers. The integration of LSTM was intended to enhance the temporal modeling of spatial feature sequences derived from CNN feature maps, especially in addressing challenges posed by inter-class similarities and class imbalance. Experimental results demonstrated that the InceptionV3 + LSTM configuration achieved the highest classification accuracy (72.01%) and consistently outperformed other models across precision, recall, and F1-score metrics. The inclusion of LSTM improved the model's ability to capture complex spatial dependencies, leading to more accurate predictions, particularly for underrepresented lesion classes such as Dermatofibroma and Vascular Lesions. Conversely, MobileNetV2 + LSTM, while marginally lower in accuracy, exhibited strong potential for lightweight, resource-efficient applications suitable for real-time mobile deployment. Confusion matrix analysis and ROC curve evaluations confirmed the models' robustness, with high true positive rates and area under the curve (AUC) scores across all diagnostic categories. The effectiveness of focal loss, class weighting, and augmentation strategies further contributed to performance improvements under data imbalance conditions.

This research highlights the significant benefits of combining CNNs with LSTM for dermatological image analysis. InceptionV3 + LSTM is best suited for high-accuracy clinical decision support, while MobileNetV2 + LSTM is recommended for scalable teledermatology applications. Future work will explore transformer-based models, attention mechanisms, and domain adaptation techniques to further advance intelligent and explainable skin disease classification systems.

DECLARATIONS

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