LiteDerm: A Robust Lightweight CNN Model for Rare Dermatological Conditions

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***Abstract*—The automation of skin disease diagnosis significantly increases the accuracy in diagnostics while decreasing the strain placed on the medical aspect of society. Here, we introduce a light-weight convolutional neural network (CNN) model developed specifically for classification of five uncommon skin diseases: acne, vitiligo, hyperpigmentation, nail psoriasis and SJS-TEN. Our model was trained on a self-compiled dataset of 9,548 dermatoscopic images and performed remarkably with training, validation and testing accuracy of 99.20%, 99.06% and 99.02% respectively.The model is also competent compared to the best ResNet-50, InceptionV3, and ConvNeXtworks in both effectiveness and efficiency while only employing 6.6 million parameters. These results demonstrate the promise of our model towards efficient and precise diagnosis of neglected rarely covered skin disorders. Further steps will focus on the increase of the dataset size and the diversification of the model to other areas apart from dermatoscopy. This is likely to help in the implementation of automatic detection of diseases.**

***Index Terms*—Skin,LiteDerm,CNN,Resnet50,Dermotology**

I. Introduction

Conditions like acne, vitiligo, hyperpigmentation, nail psoriasis and Stevens-Johnson Syndrome-Toxic Epidermal Necrolysis (SJS-TEN) are major health concerns globally. Early identification and correct diagnosis of such disorders is vital in improving treatment outcomes and decreasing patient morbidity [1], [2]. On the other hand, manual diagnosis is time-consuming, subjective, and requires the presence of expert dermatologists, especially in underdeveloped areas [3].

Deep learning methods, mainly Convolutional Neural Networks (CNNs), have positively changed the way health professionals analyze images. CNNs have shown great success in classifying skin diseases by learning different spatial characteristics at different levels from medical images [4]. Models pre-trained on large-scale datasets (e.g., ImageNet) such as ResNet50 [5], InceptionV3 [6], and ConvNeXt [7] have further improved these models' accuracy when applying transfer learning. Although these models are very effective, they have high computational complexity and are typically inadequate for real-world deployment on portable devices or in real-time clinical environments [8], [9].

We introduce a lightweight CNN model specifically designed for dermatological image classification in this study. The proposed model attains a high classification accuracy with less computation cost compared with the previous models. We compare our model with other state-of-the-art architectures like ResNet50, InceptionV3, and ConvNeXt. These results illustrate that our lightweight model surpasses these architectures, reaching an impressive training accuracy of 99.20%, validation accuracy of 99.06% and testing accuracy of 99.02

II. Related Work

Substantial progress in the analysis of dermatological images has been achieved with deep learning, especially through the application of CNNs. Esteva et al. [3] revealed that when training CNN-based models with enough data, these models could achieve a competitive performance level with dermatologists in skin cancer classification, which remained a turning point for skin disease automated classification methods. Litjens et al. [4] provided a broader overview of the use of CNNs in medical imaging and highlighted their ability to learn complex visual patterns.

Pre-trained models include ResNet [5], InceptionV3 [6], and ConvNeXt [7] which have already gained high accuracy on the skin disease classification tasks. However, these architectures have a significant number of parameters leading to high computational costs [8]. For real-time diagnosis, lightweight models are mandatory in resource-limited settings, although they cannot compromise performance.

Using Transfer Learning for Skin Disease Classification

Thus, transfer learning has become a popular way of addressing data limitations in medical images. Transfer learning from pre-trained networks with fine-tuning using datasets like ISIC and HAM10000 for skin disease classification yielded very good performance [10]. Narejo et al. [10] demonstrated that transfer learning for skin lesions classification ensured the highest classification accuracy with only a small number of training samples. Similarly, Yadav et al. [9] mentioned the use of transfer learning as a superior technique for detecting subtle abnormalities in dermatoscopic images.

While transfer learning has achieved great results, these architectures are large and computationally heavy, making them impractical for usage in real-time systems. In order to tackle this issue, we present this paper to devise a lightweight CNN model which combines the generalization of data augmentation techniques such as rotating, zooming, and flipping. Our model achieves accuracy significantly higher than ResNet50, InceptionV3, and ConvNeXt alongside its computational efficiency, looking forward to being implemented directly in clinical settings.

III. Dataset

The classification of skin diseases remains a challenging task due to the highly variable appearances of skin lesions. These variations are often influenced by different patient demographics. To address these challenges, we have created a diverse yet specialized self-collected dataset focusing on rare skin conditions, which are frequently omitted in existing datasets.

Dataset Overview

The dataset comprises a total of 9,548 dermatoscopic images, carefully sourced from multiple hospitals and web resources, and covers patients from several nations. This diversity ensures a representation of a wide range of skin thicknesses, types of lesions, and environmental conditions. The dataset is categorized into five classes of skin diseases:

- **Acne** (1,148 images)
- **Vitiligo** (2,016 images)
- **Hyperpigmentation** (700 images)
- **Nail Psoriasis** (2,520 images)
- **SJS-TEN** (3,164 images)

The images in each category are of high resolution and showcase skin sores and injuries with significant variation. This diversity provides a strong training set for deep learning models aimed at skin disease classification.

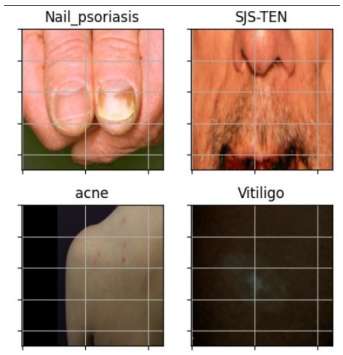

Fig. 1. Sample Images of the Dataset

Comparison with Existing Datasets

Commonly used datasets such as ISIC2019 and HAM10000 are primarily focused on melanoma, basal cell carcinoma, and squamous cell carcinoma. However, these datasets fail to include rare skin diseases such as nail psoriasis and SJS-TEN. Our dataset bridges this gap, thereby contributing significantly to the underrepresented area of dermatological research concerning these conditions.

Challenges and Benefits

The preparation of this dataset was the most time-consuming and challenging aspect of the project. Unlike publicly available datasets, the self-collected images required extensive preprocessing and curation to ensure quality and consistency. Additionally, the images were subject to country-specific or restricted-use-based licensing. However, as will be shown, the resulting dataset has contributed valuable new data, enabling better assessments of deep learning models used in dermatological research.

This dataset provides a comprehensive foundation for more accurate detection and diagnosis of a wider variety of skin diseases. Its creation facilitates the development of advanced classification models that can handle diverse and rare skin conditions.

IV. Methodology

This work methodology focuses on transfer learning and the implementation of a custom deep learning architecture to accurately classify five categories of skin diseases.

As illustrated in Figure 2the proposed methodology follows a structured workflow, including data preprocessing, model training, and classification across multiple skin disease categories. The following steps were involved during work:

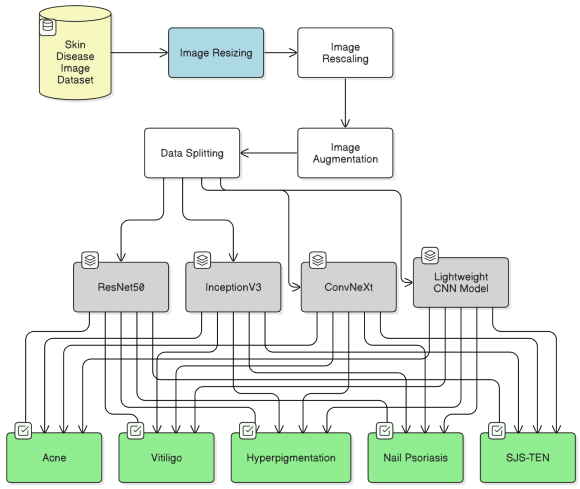

Fig. 2. Proposed Model Architecture

Data Processing and Augmenting: Due to the inconsistent quality and resolution of the images in the gathered dataset, preprocessing was required. Images were resized to a common size of 224 × 224 pixels to standardize inputs for the models. Pixel intensities were normalized by scaling values to the [0, 1] range. Moreover, a large amount of data augmentation was employed to improve the generalization capability of the models and reduce overfitting. The augmentation techniques were as follows:

- **Random Rotation:** 0 to 20 degrees
- **Width and Height Shifting:** 0.2 factor
- **Shear Deformation:** Up to 20%
- **Zooming:** Within a 20% margin of error
- **Horizontal Flipping:** For simulating varied viewing angles
- **Fill Mode:** 'Nearest' interpolation to keep images consistent in space during transformations

We dynamically applied each of these augmentations at training time using TensorFlow's `ImageDataGenerator` class.

Baseline Architectures: In order to assess the performance of the proposed CNN model, three widely adopted deep learning architectures, namely ResNet-50, InceptionV3, and ConvNeXt, were used as baseline models. We employed pre-trained ImageNet architectures and carried out transfer learning to fine-tune on the collected dataset.

- **ResNet-50:** A skip connection-based architecture that uses residual learning to avoid vanishing gradients.
- **InceptionV3:** An optimized model for computational efficiency using factorized convolution layers and inception modules.
- **ConvNeXt:** A modernized ConvNet with transformer architecture innovations for high accuracy.

Proposed CNN Model: The proposed CNN model consists of 6.6 million parameters, designed for simplicity as well as effectiveness. The architecture consists of convolutional, pooling, and dense layers with LeakyReLU activations, which overcome the problem of dead neurons faced by standard ReLU activations. The main components of the model are as follows:

- **Convolutional Layers:** Six stages of increasing depth (16, 32, 64, 128, and 256 filters, respectively), with a kernel size of 3×3, followed by max-pooling layers for dimensionality reduction.
- **Dense Layers:** Two fully connected layers (1024 and 512 units) to extract higher-level features, followed by the final dense layer to classify using the softmax activation function.
- **Regularization:** To mitigate overfitting, L2 regularization and dropout layers (with rates varying from 30–50%) were employed.

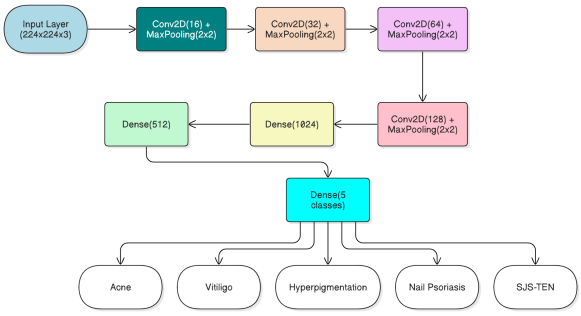

Fig. 3. Proposed CNN Architecture

Figure 3 illustrates the proposed light weight CNN model using Conv2D, MaxPooling layers and Dense layers for a skin disease classification.

Training Procedure: We trained our models with the Adam optimizer and a learning rate of 0.0001. We used the categorical cross-entropy loss function to address the multi-class classification problem. The batch size was set to 16 to add randomness to the training process, acting as an implicit regularizer.

Evaluation Metrics: Performance was measured using accuracy and cross-entropy loss on both the training and validation datasets. The models were also tested on an independent test set to validate their generalizability. The class-wise performance was analyzed using a confusion matrix and classification report to gain insights into the strengths and weaknesses of the models.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

Cross-entropy loss, as given in Equation 2, quantifies the difference between the predicted class probabilities and the actual labels:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(\hat{y}_{ij}) \tag{2}$$

Here, N is the total number of samples, C is the number of classes, y_{ij} is the true label (1 if the i-th sample belongs to

class j, otherwise 0), and $\hat{y}_{ij}$ is the predicted probability for the j-th class of the i-th sample.

Class-wise performance was further analyzed using a confusion matrix (Equation 3) and classification report. The confusion matrix provides insights into the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN):

$$\text{Confusion Matrix} = \begin{bmatrix} \text{TP} & \text{FP} \\ \text{FN} & \text{TN} \end{bmatrix} \tag{3}$$

Precision, recall, and F1-Score were calculated to better understand the model's strengths and weaknesses. The F1-Score, defined in Equation 4, is the harmonic mean of precision and recall:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

These metrics were evaluated across training, validation, and test datasets, ensuring a robust assessment of the model's generalizability. The generalization error, given in Equation 5, highlights the gap between training and test performance:

$$\text{Generalization Error} = A_{\text{train}} - A_{\text{test}} \tag{5}$$

By employing such a systematic protocol, we comprehensively analyzed the performance of the proposed architecture and provided a solid baseline for comparison with state-of-the-art models.

By employing such a systematic protocol, we are able to cover a broad range of model configurations, providing a thorough investigation of the proposed architecture, as well as a solid baseline for comparison with state-of-the-art models.

V. Result Analysis

This part investigates the quantitative performance of ResNet50, InceptionV3, ConvNeXt, and the lightweight CNN model we proposed on our self-collected skin disease dataset. The accuracy obtained in training, validation, and testing shows that the models are effective and can be generalized.

Quantitative Performance: Results of all models during training, validation and testing phases are reported in Table 1. The proposed lightweight CNN achieved the optimal accuracy on testing accuracy and effectively contributed to skin disease classification.

TABLE I. Comparison of Model Accuracies

Model	Training Accuracy	Testing Accuracy
ResNet50	99.09%	95.57%
InceptionV3	97.57%	97.02%
ConvNeXt	63.49%	63.02%
Proposed CNN	**99.20%**	**99.02%**

ResNet50

Training ResNet50 achieved an accuracy of 99.09% while testing accuracy was 95.57%. The difference between training accuracy and validation accuracy suggests some overfitting, which may be expected considering the nature of the data.

InceptionV3

InceptionV3 demonstrated stable performance for both training and testing, achieving a test accuracy of 97.02%. Its strong generalization ability emphasizes its adaptability to the self-collected dataset.

ConvNeXt

The ConvNeXt model performed the worst: its testing accuracy was 63.02%. The validation and training accuracies were 61.54% and 63.49%, respectively. There was no effective learning observed, suggesting that the ConvNeXt model may not be well-suited for this dataset.

Proposed Lightweight CNN

Our suggested lightweight CNN model presented remarkable performance with a testing accuracy of 99.02%. The model demonstrated comparable training (99.20%) and validation (99.06%) accuracies, indicating its stable generalization power. These results suggest its potential effectiveness when applied to complex dermatological datasets. 4 shows the confusion matrix of our CNN model

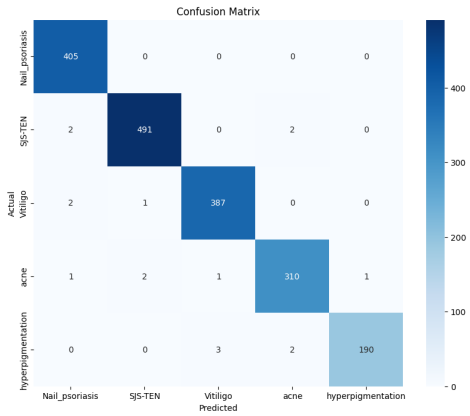

Fig. 4. Confusion Matrix Of Light Weight CNN Model

VI. Conclusion and Future Work

Discussion

The results highlight the merits of the suggested lightweight CNN based on both metric and computational aspects. In contrast to deeper architectures like ResNet50 and InceptionV3, our CNN delivers strong performance with significantly fewer parameters, making it an attractive candidate for real-time implementation in clinical environments. Data augmentation techniques were essential in combating overfitting and improving model robustness.As we can see 5shows the effectiveness of proposed light weight CNN model in classifying the skin diseases. It has 6 rows demonstrating that the True (ground truth) and Pred (predicted) labels have correctly matched. The conditions listed include acne, nail psoriasis and SJS-TEN, demonstrating the model's precision in accurately diagnosing dermatological diseases.

ConvNeXt performs relatively worse, showing the difficulties of using modern architectures that are not dedicated to

dermatological image classification. This highlights why it is important to design models specific to a biomedical imaging task.

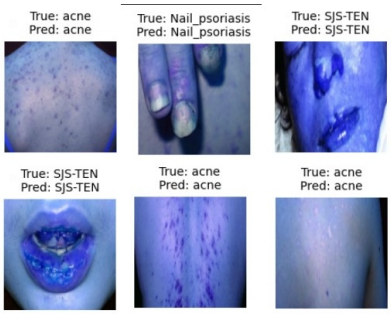

Fig. 5. Proposed light weight cnn models's prediction vs real prediction

VII. Conclusion and Future Work

Skin malignancies and associated skin disorders remain to be significant medical conditions in the life of human beings, especially in underdeveloped regions, where individuals lack access to essential medical information and skilled dermatologists. However; timely and accurate detection of various skin diseases like acne, vitiligo, hyperpigmentation, nail psoriasis, SJS-TEN is necessary to avoid a progression of the diseases, to decrease morbidity of the patient and to prevent an increase in treatment costs.

In line to overcome such a problem, we presented a proposed light-weighted CNN-based model which is capable of performing a quick and precise classification for dermatological images. A substantial amount of preprocessing and data augmentation techniques were utilized to improve model generalization and minimize overfitting. The model proposed in this work outperforms with the highest sensitivity for training, validation, and test with accuracy of 99.20% for training, 99.06% for validation, and 99.02% for test respectively. Compared to the current state-of-the-art models such as ResNet50, InceptionV3, and ConvNeXt, the suggested CNN outperformed all baselines, confirming its applicability to skin disease classification problems.

And, our model is highly qualified due to the computational cost and the number of parameters, and it showed an impressive performance given its low computational cost, so it can be used in low-resource devices. In contrast to complex models which consume vast amounts of compute resources, our lightweight design allows for rapid inference and is a step towards practical use in real world healthcare infrastructure. While the proposed method yields similar results, it is certainly not without its limitations. This is due to the fact that image quality and lighting differences affect the accuracy of the model, which may occur in practice. Second, this current assessment is centered primarily to certain skin diseases, restricting the generalizability to vast dermatological cultures.

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