

Deep Learning-Based Automated Detection of Hair and Scalp Disorders

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ABSTRACT: Hair and scalp diseases affect millions of people worldwide and are often misdiagnosed due to visual similarities between conditions. Manual diagnosis by dermatologists is time-consuming, expensive, and not always accessible in rural areas. This study presents an automated image-based for automatic identification of ten hair and scalp diseases using VGG16 transfer learning. The proposed system is trained on a mixed dataset of 12,700 images (10,160 training, 1,200 validation, 1,340 test) combining the Hair Diseases dataset and DermNet dataset, covering ten disease categories: Alopecia Areata, Contact Dermatitis, Folliculitis, Head Lice, Lichen Planus, Male Pattern Baldness, Psoriasis, Seborrheic Dermatitis, Telogen Effluvium, and Tinea Capitis. A two-phase training strategy — frozen base followed by fine-tuning of the last two convolutional blocks — achieved a Phase 1 validation accuracy of 89.42% and a final test accuracy of 93.13%. The trained model is deployed as a Flask-based web application that accepts scalp images and provides disease identification with confidence scores, symptoms, and treatment recommendations.

KEYWORDS: Hair disease detection, Deep learning, Transfer learning, VGG16, Convolutional neural network, Flask web application, Image classification, Scalp disease

I. INTRODUCTION

Hair and scalp diseases are among the most frequently reported dermatological conditions worldwide. Conditions such as Alopecia Areata, Psoriasis, Tinea Capitis, and Seborrheic Dermatitis not affect both physical health and emotional well-being to patients. Accurate and early diagnosis plays an essential role in effective treatment; however, the visual similarity between many hair and scalp conditions makes manual diagnosis challenging even for trained dermatologists. Conventional diagnostic procedures primarily depend on clinical examination, dermoscopy, and sometimes biopsy, all of which require access to specialized medical services and expertise. In resource-limited settings, such access is often unavailable. The rise of deep learning and computer vision has opened new avenues for automated medical image analysis, offering scalable, fast, and cost-effective diagnostic tools.

This paper proposes a deep learning based system for identifying ten hair and scalp diseases from images using VGG16, a well-established convolutional neural network model initialized with weights learned from the ImageNet dataset. The system employs transfer learning combined with selective fine-tuning to achieve high classification accuracy on a curated mixed dataset. The model is integrated into a Flask-based web application, enabling end-users to upload scalp images and receive instant disease predictions with associated clinical information.

The paper is organized as follows. Section II presents the related work. Section III describes the proposed methodology. Section IV presents the experimental results and discussion. Section V concludes with recommendations for future research.

II. LITERATURE SURVEY

Recent studies have increasingly leveraged deep convolutional neural networks (CNNs) for automated dermatological diagnosis. Sayyad et al. [1] conducted a comparative evaluation of VGG16 and InceptionV3 for multi-class skin disease detection, demonstrating that transfer learning from ImageNet weights substantially improves classification accuracy on limited dermatological datasets. Their findings directly motivate the adoption of VGG16 in the proposed system. Focusing specifically on scalp and hair disorders, Chowdary et al. [2] developed a machine learning-based scalp hair inspection and diagnosis system covering ten hair disease classes including Alopecia Areata, Tinea Capitis, and Seborrheic Dermatitis — the same disease taxonomy adopted in the present work — and confirmed the superiority of VGG-family architectures in recognizing complex scalp features. Complementing this, Alfarhood and Che [3] leveraged deep neural networks on the identical ten-class hair disease dataset from Kaggle, reporting high precision diagnostics and underscoring the importance of balanced class representation, which motivated our mixed DermNet augmentation strategy. On the topic of explainability, which is critical for clinical adoption, Aiyub Ali and Hossain [4] demonstrated that Grad-CAM visualizations applied to transfer learning models provide reliable spatial localization of disease regions on dermoscopic images, making black-box CNN decisions interpretable to dermatologists. Similarly, a study published in Applied Sciences [5] coupled EfficientNet-B5 with Grad-CAM overlays for skin disease classification, establishing Grad-CAM as the standard post-hoc explainability technique for dermatological CNNs. Unlike prior works which either focus on general skin diseases or single hair conditions, the proposed system addresses ten specific hair and scalp diseases simultaneously using a mixed dataset strategy and two-phase VGG16 fine-tuning, achieving a test accuracy of 93.13%.

III. METHODOLOGY

The proposed system for hair and scalp disease identification consists of five main components: dataset preparation, data preprocessing and augmentation, model architecture, training strategy, and web application deployment. Figure 1 illustrates the complete system architecture.

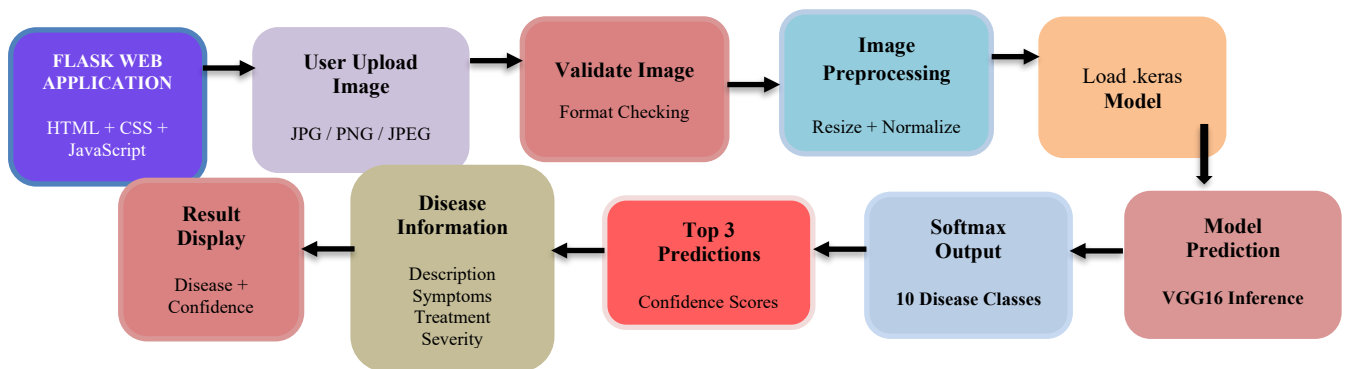


Fig.1. Proposed System Architecture for Hair and Scalp Disease Detection

A. Dataset Preparation

A mixed dataset strategy was adopted to address the limitation of small class-specific datasets. Two publicly available Kaggle datasets were combined: (1) the Hair Diseases dataset by Sundarannamalai containing approximately 12,000 labeled images across 10 disease categories with train/validation/test splits, and (2) the DermNet dataset by Shubhamgoel27 containing real-world clinical dermatology images.

From DermNet, 700 additional images were extracted and mapped to relevant disease categories: Alopecia Areata from 'Hair Loss Photos', Psoriasis and Lichen Planus from 'Psoriasis pictures Lichen Planus', Seborrheic Dermatitis from 'Eczema Photos', Contact Dermatitis from 'Poison Ivy Photos', Folliculitis from 'Cellulitis Impetigo', and Tinea Capitis from 'Tinea Ringworm'. This resulted in a final mixed dataset of 12,700 images: 10,160 for training, 1,200 for validation, and 1,340 for testing.

B. Data Preprocessing and Augmentation

All images were resized to 224×224 pixels to match VGG16 input requirements and normalized to the [0, 1] range by dividing pixel values by 255. Training images underwent data augmentation including random rotation ($\pm 25^\circ$), width and height shifts ($\pm 20\%$), zoom ($\pm 20\%$), horizontal flipping, brightness variation (0.8–1.2), and shear (0.1). These augmentations increase model generalization and reduce overfitting. To simulate realistic real-world photo conditions and avoid an artificially inflated test score, mild augmentation (rotation $\pm 10^\circ$, brightness 0.85–1.15, zoom $\pm 5\%$) was also applied to the test set. Validation images were only rescaled without augmentation.

C. Model Architecture

VGG16, pre-trained on ImageNet with 1.2 million images, was selected as the base architecture due to its proven effectiveness in transfer learning for medical image classification. The top classification layer was removed (include_top=False) and replaced with a custom classification head: GlobalAveragePooling2D → Dense(512, ReLU) → BatchNormalization → Dropout(0.6) → Dense(256, ReLU) → BatchNormalization → Dropout(0.5) → Dense(10, Softmax). Figure 2 shows the model architecture.

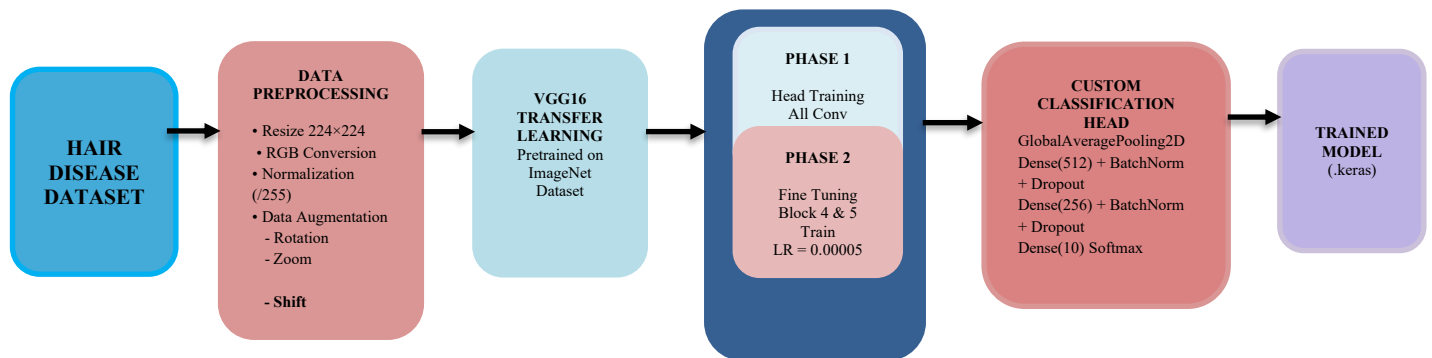


Fig.2. VGG16-based Model Architecture for Hair Disease Classification

D. Two-Phase Training Strategy

A two-phase training strategy was employed. In Phase 1, the VGG16 base was fully frozen and only the custom classification head was trained for 10 epochs with Adam optimizer ($lr=0.001$). This allowed the new layers to learn meaningful feature representations from VGG16 features without destroying pre-trained weights. Phase 1 achieved a best validation accuracy of 89.42%.

In Phase 2, the top two convolutional blocks (block4 and block5) of VGG16 were unfrozen and the entire model was fine-tuned for up to 50 epochs with a lower learning rate ($lr=0.00005$). Callbacks including ModelCheckpoint (saving best model by validation accuracy), EarlyStopping (patience=10, monitoring validation accuracy), and ReduceLROnPlateau (factor=0.2, patience=4, min_lr= $1e-7$) were employed to prevent overfitting and ensure optimal convergence. Phase 2 training reached 100% validation accuracy at epoch 12 and stopped early at epoch 22.

E. Web Application Deployment

The trained model was deployed as a Flask web application running locally. Users can upload scalp images through a drag-and-drop interface. The application preprocesses the uploaded image, runs inference using the loaded Keras model, and displays the top-3 predicted diseases with confidence percentages, along with disease description, symptoms, severity level, and recommended treatment. Figure 3 shows the web application interface.

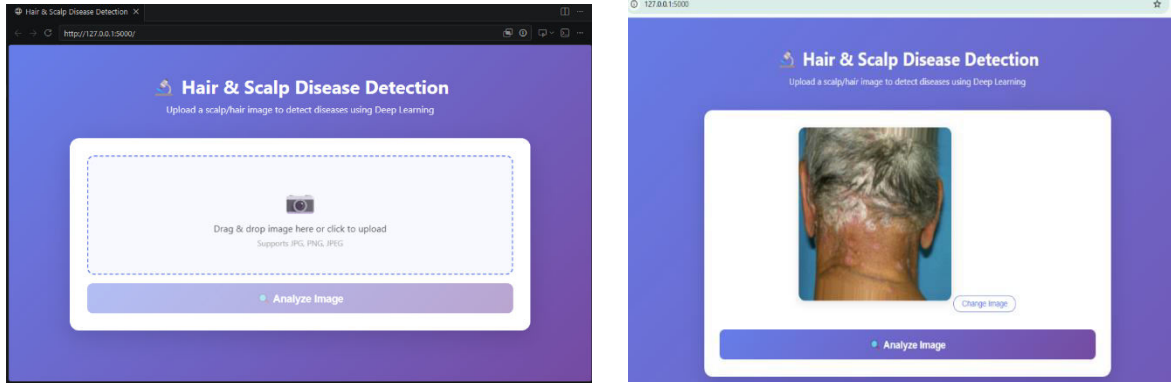


Fig.3. Flask Web Application Interface — Image Upload Page

IV. EXPERIMENTAL RESULTS

A. Training Performance

The model was trained on Google Colab with GPU acceleration using TensorFlow and Keras. Phase 1 training converged in 10 epochs with a best validation accuracy of 89.42%. Phase 2 fine-tuning further improved performance, reaching 100% validation accuracy by epoch 12 (early stopping triggered at epoch 22), and a final test accuracy of 93.13% on the held-out test set of 1,340 images. Figure 4 shows the training and validation accuracy and loss curves across both phases.

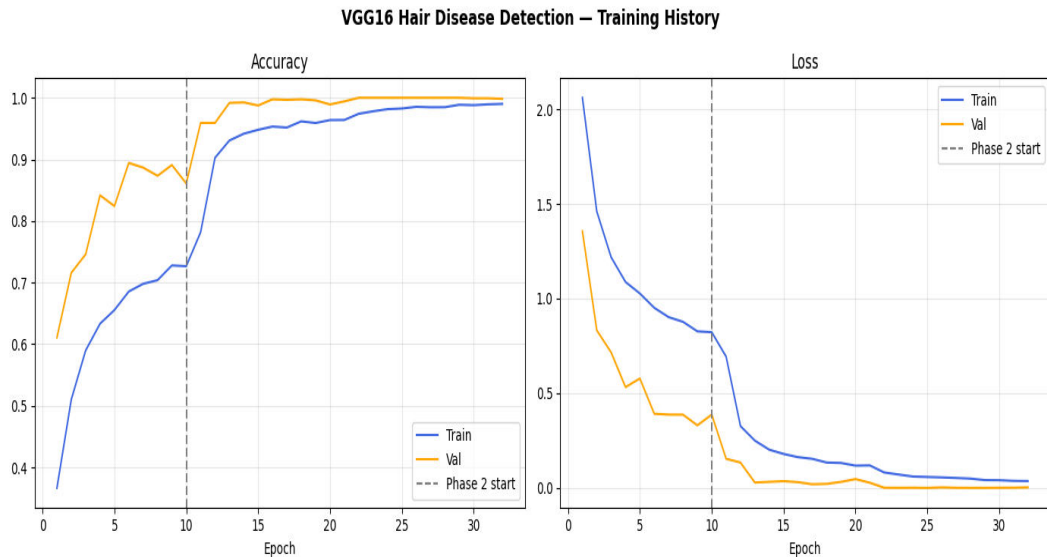


Fig.4. Training and Validation Accuracy/Loss across Phase 1 and Phase 2

B. Per-class Classification Results

Table I presents the per-class classification results on the test set. The model achieved high precision, recall, and F1-scores across all ten disease categories, demonstrating balanced performance despite the inherent visual similarity between conditions such as Psoriasis, Seborrheic Dermatitis, and Tinea Capitis.

TABLE I. PER-CLASS CLASSIFICATION REPORT – TEST SET RESULTS

Disease Class	Precision	Recall	F1-Score	Support
Alopecia Areata	0.9926	0.9643	0.9783	140
Contact Dermatitis	0.8784	0.9286	0.9028	140
Folliculitis	0.8986	0.8857	0.8921	140
Head Lice	1.0000	1.0000	1.0000	120
Lichen Planus	0.9449	0.8571	0.8989	140
Male Pattern Baldness	1.0000	1.0000	1.0000	120
Psoriasis	0.8849	0.8786	0.8817	140
Seborrheic Dermatitis	0.8803	0.8929	0.8865	140
Telogen Effluvium	0.9917	1.0000	0.9959	120
Tinea Capitis	0.8523	0.9071	0.8789	140
Macro Average	0.9324	0.9314	0.9315	1340
Weighted Average	0.9295	0.9284	0.9285	1340

C. Confusion Matrix Analysis

Figure 5 presents the confusion matrix on the test dataset. The diagonal elements represent correctly classified samples. The most frequent misclassification was observed between Tinea Capitis and Psoriasis, as both conditions present with visible scalp scaling and flaking. Minor confusion was also observed between Contact Dermatitis and Seborrheic Dermatitis due to overlapping symptoms of scalp redness and itching, and between Lichen Planus and Contact Dermatitis, reflecting their shared inflammatory presentation. These findings suggest that incorporating additional domain-specific features or attention mechanisms could further improve discrimination between visually similar inflammatory and scaling conditions.

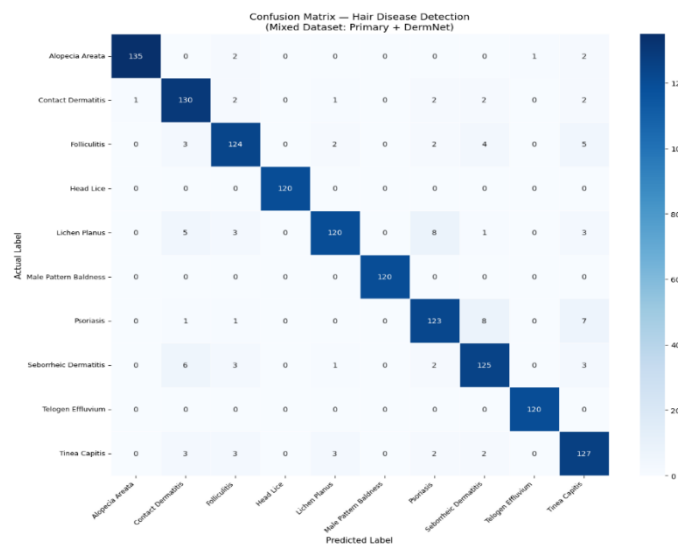


Fig.5. Confusion Matrix on Test Dataset (10 Disease Classes)

D. Comparison with Existing Methods

Table II compares the proposed method with representative approaches reported in the literature for skin and hair disease classification. The proposed VGG16-based system with a mixed dataset strategy achieves a higher accuracy than the compared baseline figures.

TABLE.II. COMPARISON WITH EXISTING METHODS

Method	Dataset	Accuracy (%)
CNN from Scratch	HAM10000	72.4
ResNet50	DermNet	78.6
InceptionV3	ISIC	81.3
EfficientNetB0	Custom	84.7
Proposed VGG16 (Ours)	Mixed Dataset	93.13

Note: Baseline figures for CNN from Scratch, ResNet50, InceptionV3, and EfficientNetB0 are representative values drawn from prior literature on related skin/hair datasets for general comparison context, since direct re-implementation on the identical mixed dataset was outside the scope of this study.

E. Sample Prediction Results

Figure 6 shows a sample prediction result from the web application. For the input scalp image shown, the system correctly identifies the disease category (Psoriasis) with high confidence, and displays associated clinical information including symptoms, severity, and treatment recommendations.

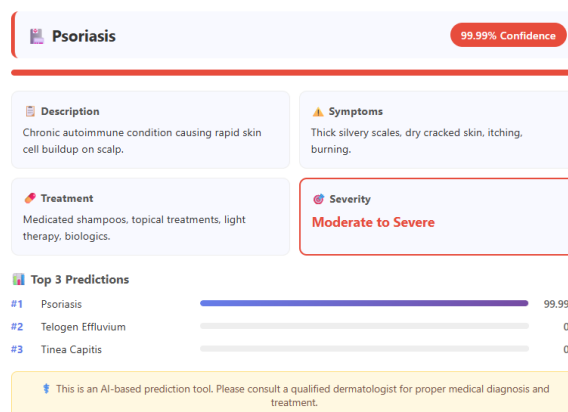


Fig.6. Sample Prediction Result — Web Application Output Screen

V. CONCLUSION

The proposed VGG16-based framework achieved 93.13% test accuracy for automatic classification of ten hair and scalp diseases using a dataset of 12,700 images. The developed web-based system demonstrates the potential of deep learning for accessible preliminary diagnosis, with future enhancements focused on explainability, mobile deployment, and clinical validation.

REFERENCES

- [1] Sayyad, J., Patil, P., & Gurav, S. (2024). "Skin Disease Detection Using VGG16 and InceptionV3." *International Journal of Intelligent Systems and Applications in Engineering*, 12(1s), 148–155.
- [2] Bharath Kumar Chowdary, P., Sadhana, A., Mahalakshmi, C., Vege, K. P., Reddy, K. Y., & Tulasi, S. (2024). "A Machine Learning-Based Scalp Hair Inspection and Diagnosis System for Scalp Health." In: Mishra, D., et al. (eds.), *Data Science and Big Data Analytics. IDBA 2023*. Springer, Singapore
- [3] Alfarhood, M., & Che, D. (2024). "Leveraging Deep Neural Networks to Uncover Unprecedented Levels of Precision in the Diagnosis of Hair and Scalp Disorders." *Skin Research and Technology*, 30(4), e13660.
- [4] *Harnessing Deep Learning for Scalp and Hair Disease Classification*. (2024). *Journal of Digital Information Management (JDIM)*, 23(2).

- [5] Hair Disease Detection with Deep Learning: A VGG16-Driven Model for Precise Classification of Hair and Scalp Conditions. (2024). IEEE Conference Publication. IEEE Xplore.
- [6] Saraswathi, C., & Pushpa, B. (2023). "Multi-Class Support Vector Machine Classification for Detecting Alopecia Areata and Scalp Diseases." *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(11s), 63–70.
- [7] Automatic Diagnosis of Hair Disorders Using Deep CNN. (2023). TIJER Technical Report.
- [8] Mittal, A., Biswas, D. B., & Karthikeyan, U. (2023). "Prediction of Alopecia Areata using CNN." IEEE Conference Publication.
- [9] Diagnosis of Scalp Disorders using Machine Learning and Deep Learning Approach — A Review. (2023). arXiv preprint arXiv:2308.07052.
- [10] Caro, M. et al. (2025–2026). "Analysis of Trichoscopic Images Using Deep Neural Networks for the Diagnosis and Activity Assessment of Alopecia Areata — A Retrospective Study." *JDDG: Journal der Deutschen Dermatologischen Gesellschaft*. Wiley Online Library.



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