Analysis of Human Hair Follicles in Scalps Using AIML and Image Processing

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Abstract— Hair and scalp disorders have become increasingly prevalent due to modern lifestyle changes, stress, pollution, and improper hair care practices. Early diagnosis plays a vital role in preventing severe hair loss and scalp damage. However, conventional diagnosis methods rely on manual inspection by dermatologists, which is time-consuming, subjective, and costly. This project presents an automated system for detecting and classifying human scalp and hair disorders using Artificial Intelligence (AI), Machine Learning (ML), and Image Processing techniques. The proposed system uses image preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), noise removal, and image sharpening to enhance scalp images. A Convolutional Neural Network (CNN) based deep learning model, MobileNetV2, is employed for classification due to its lightweight architecture and high computational efficiency. The dataset used for training and testing consists of multiple classes of scalp conditions collected from a publicly available Kaggle dataset. Experimental results demonstrate a high classification accuracy of 99.8%, indicating the effectiveness of the proposed approach. The system has potential applications in early diagnosis, dermatological assistance, and telemedicine platforms. Future work includes deploying the model as a fully functional web application and expanding the dataset for improved robustness.

Index Terms— Scalp Disease Detection, Deep Learning, MobileNetV2, Image Processing, AI in Healthcare

I. Introduction

Hair and scalp health plays a vital role in an individual's overall appearance, confidence, and well-being. In recent years, hair-related disorders have become increasingly common due to stress, lifestyle changes, environmental pollution, hormonal imbalance, and improper hair care practices. Traditional diagnosis relies on manual dermatological examination, which is time consuming.

With the advancement of Artificial Intelligence and image processing techniques, automated medical image analysis has emerged as an effective solution. This work proposes an AI-based automated system for detecting and classifying multiple scalp and hair disorders using deep learning techniques to improve diagnostic accuracy and accessibility.

II. Literature Review

Seyedali Minaee, Yuri Boykov, Fatih Porikli, Antonio Plaza, Nasser Kehtarnavaz, and Demetri Terzopoulos published a comprehensive survey titled "Image Segmentation Using Deep Learning: A Survey" in IEEE Transactions on Pattern Analysis and Machine Intelligence in 2022. This paper reviewed state-of-the-art deep learning architectures used for medical image segmentation and classification. The authors discussed convolutional neural networks, encoder–decoder models, and lightweight architectures suitable for medical applications. The survey highlighted that deep learning models outperform traditional image processing techniques in extracting complex visual patterns from medical images, which supports their application in scalp and hair disorder analysis.

Hala A. Abbas, Mohammed A. Eltoukhy, and Ahmed S. El-Sherif presented a review titled "Automated Diagnosis of Skin Diseases Using Deep Learning: A Review", published in Computers in Biology and Medicine in 2022. This study analysed various deep learning approaches used for diagnosing skin diseases from image data. The authors emphasized the role of convolutional neural networks in achieving high diagnostic accuracy and reducing dependency on manual clinical examination. The review identified challenges such as dataset quality, class imbalance, and real-time deployment, which are also relevant in scalp disease detection systems.

Rosawan Thuangtong, Wasan Wasan, Kanchanatawan Kanchanatawan, Kornkanok Chaiyakul, Chaiwat Rattanaporn, and Peerapong Jarupoonphol published a study titled "Development and Evaluation of an Integrated Image-Guided Robotic System for Hair Transplant Surgery" in 2024 through ScienceDirect by Elsevier. The authors developed an intelligent robotic system guided by image processing techniques to automate hair follicle extraction during transplant procedures. Experimental results showed improved precision and reduced human intervention. Despite its effectiveness, the system required specialized robotic hardware and was limited to surgical environments, reducing its applicability for general scalp disease diagnosis.

From the reviewed literature, it is observed that existing research primarily focuses on hair follicle detection, robot-assisted hair transplantation, or general skin disease diagnosis. Limited work has been carried out on developing a lightweight, multi-class scalp disease classification system that can operate in real time and be accessed through a web-based interface. Additionally, many systems rely on specialized hardware or lack user-friendly deployment mechanisms.

III. METHODOLOGY

The proposed system follows a systematic pipeline consisting of image acquisition, preprocessing, feature extraction, classification using a deep learning model, and result generation. Each stage of the methodology is carefully designed to ensure accuracy, efficiency, and reliability in real-time scalp disease detection.

The overall methodology of the proposed system is illustrated through a block diagram that represents the sequential flow of operations involved in model preparation and deployment. The major stages include image acquisition, preprocessing, classification, and output result generation.

Fig. 1. Block Diagram of Model Preparation

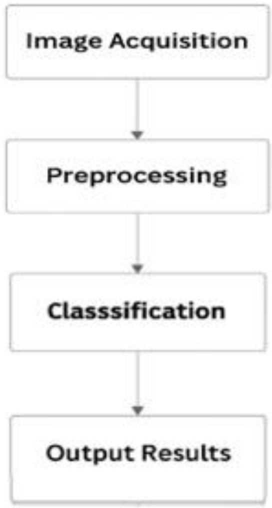


Image acquisition is the first and most critical step in the proposed methodology. In this stage, scalp images are captured using a high-resolution digital camera or mobile device under proper lighting conditions. These images serve as the input to the system.

The acquired images contain visual information related to hair follicles, scalp texture, and disease patterns such as dandruff, alopecia, folliculitis, and other scalp disorders. All images are stored in RGB format and later resized to match the input requirements of the deep learning model.

Purpose Of Image Acquisition:

- Capture real-time scalp images
- Ensure sufficient visual clarity of hair follicles
- Provide raw data for further processing

Image Preprocessing

Preprocessing improves the quality of the captured images and prepares them for efficient feature extraction and classification. Raw images often contain noise, uneven illumination, and varying resolutions, which can negatively affect model performance.

Noise Removal Using Gaussian Filter

Noise removal is performed using a Gaussian filter, which smoothens the image while preserving important structural details.

The Gaussian filter is defined as:

$$G(x, y) = (1 / (2\pi\sigma^2)) \cdot \exp(-(x^2 + y^2) / (2\sigma^2)) \quad (1)$$

Where:

- σ = standard deviation controlling the smoothing level
- x,y = spatial coordinates

This filter reduces high-frequency noise caused by camera sensors and lighting variations.

Brightness And Contrast Adjustment

Brightness and contrast normalization enhances visibility of hair follicles and scalp texture. This ensures uniform intensity distribution across images.

Contrast adjustment is performed using:

$$I\_new = \alpha \cdot I\_old + \beta \quad (2)$$

Where:

- α = contrast control
- β = brightness offset

Image Resizing And Normalization

All images are resized to 224 × 224 × 3, which is the required input size for the MobileNetV2 model.

Pixel normalization is applied as:

$$I\_norm = (I - I\_min) / (I\_max - I\_min) \quad (3)$$

This ensures faster convergence during training.

Model Selection – Mobilenetv2

MobileNetV2 is a lightweight convolutional neural network architecture specifically designed for real-time and resource-constrained environments such as mobile devices and web-based applications.

The reasons for selecting MobileNetV2 include:

- Low computational cost
- Reduced number of parameters
- High classification accuracy
- Fast inference time
- Suitable for real-time medical image analysis

MobileNetV2 improves upon MobileNetV1 by introducing:

- Depth-wise separable convolutions
- Inverted residual blocks
- Linear bottlenecks

IV. Results and Discussions:

The experiments were conducted using the Kaggle Hair Disease Dataset, which contains labeled scalp images belonging to eleven different classes. The dataset was divided into training, validation, and testing subsets in the ratio of 45% : 10% : 45% respectively. All images were resized to 224 × 224 × 3 to match the input requirements of the MobileNetV2 architecture.

The model was trained using the Adam optimizer with a learning rate of 1×10^{-4} and categorical cross-entropy as the loss function. Training was performed for 50 epochs, with early stopping applied to prevent overfitting. Mixed precision training was enabled to improve training speed and reduce memory consumption.

Training And Validation Performance

During the training phase, the model showed a consistent improvement in accuracy with a corresponding decrease in loss. Validation accuracy closely followed training accuracy, indicating good generalization and minimal overfitting.

Fig. 2. Training and Validation Accuracy vs Epochs

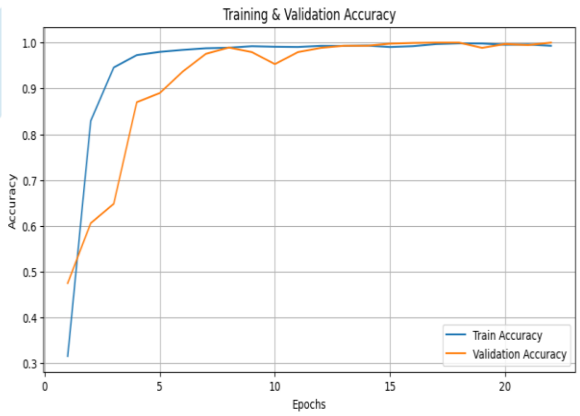
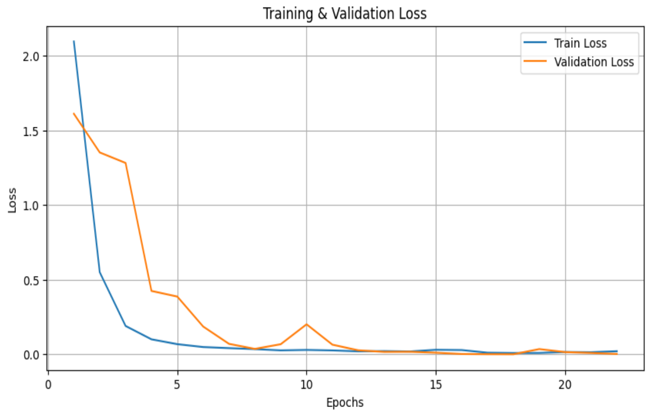


Fig. 3. Training and Validation Loss vs Epochs



Discussion

- The steady increase in training accuracy indicates effective feature learning by the MobileNetV2 model.
- The close alignment between training and validation curves confirms that the model generalizes well to unseen data.
- Early stopping helped in avoiding overfitting by halting training when validation loss stopped improving.

Classification Accuracy

The final trained model achieved an overall classification accuracy of **99.8%** on the test dataset. This high accuracy demonstrates the robustness of the proposed system in distinguishing between healthy scalp conditions and various hair disorders.

Table 1. Overall Model Performance

METRIC	VALUE
Accuracy	99.8%
Precision	1.00
Recall	1.00
F1-Score	1.00

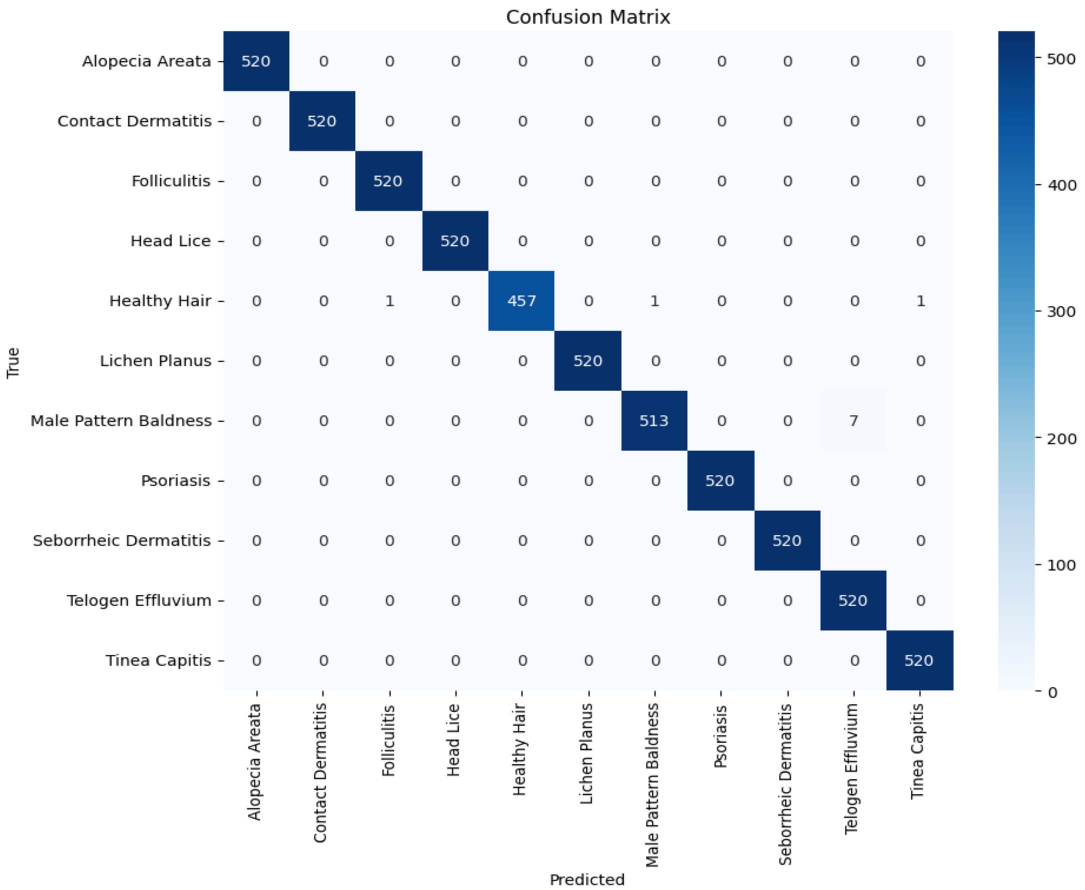
Discussion

- The high accuracy confirms that the model effectively captures discriminative features related to scalp and hair follicle conditions.
- Precision and recall values indicate low false positive and false negative rates, which is critical in medical diagnosis applications.

Confusion Matrix Analysis

A confusion matrix was generated to analyse the class-wise performance of the proposed model. It provides insights into correct and incorrect classifications across all scalp disease categories.

Fig . 4. Confusion Matrix for Scalp Disease Classification



Discussion

- Most classes show strong diagonal dominance, indicating correct classification.
- Minor misclassifications may occur between visually similar conditions, which is expected in medical image analysis.
- Overall, the confusion matrix confirms the reliability and consistency of the proposed approach.

Disease-Wise Performance Evaluation

The system successfully classified multiple scalp and hair disorders.Each class achieved high recognition accuracy due to balanced dataset distribution and effective feature extraction by MobileNetV2.

Table 2. Class-Wise Accuracy

Class Name	Precision	Recall	F1-Score	Support
Alopecia Areata	1.00	1.00	1.00	520
Contact Dermatitis	1.00	1.00	1.00	520
Folliculitis	1.00	1.00	1.00	520
Head Lice	1.00	1.00	1.00	520
Healthy Hair	1.00	0.99	1.00	460
Lichen Planus	1.00	1.00	1.00	520
Male Pattern Baldness	1.00	0.99	0.99	520
Psoriasis	1.00	1.00	1.00	520
Seborrheic Dermatitis	1.00	1.00	1.00	520
Telogen Effluvium	0.99	1.00	0.99	520
Tinea Capitis	1.00	1.00	1.00	520

V. Conclusion

In this work, a comprehensive and systematic approach was adopted to develop an end-to-end scalp disease detection system. The methodology begins with image acquisition, followed by pre-processing techniques such as noise removal, brightness and contrast enhancement, resizing, and normalization to ensure consistent and high-quality input data. These pre-processing steps significantly improved the visibility of scalp features and hair follicle patterns, thereby enhancing the effectiveness of the subsequent classification process.

A well-structured dataset consisting of eleven clinically relevant scalp and hair disease classes was used to train and evaluate the model. The dataset was carefully divided into training, validation, and testing subsets to ensure fair evaluation and to prevent overfitting. Balanced class distribution further contributed to improved learning and unbiased performance across all disease categories.

The core strength of the proposed system lies in the use of the MobileNetV2 deep learning architecture, which was selected due to its lightweight design, reduced computational complexity, and high classification accuracy. Advanced concepts such as depth wise separable convolutions, inverted residual blocks, and batch normalization enabled efficient feature extraction while maintaining minimal resource usage. Fine-tuning of the pretrained model further improved its ability to capture disease-specific visual patterns present in scalp images.

Extensive experimentation and evaluation demonstrated the effectiveness of the proposed approach. The model achieved an overall classification accuracy of 99.8%**,** with high precision, recall, and F1-score values across all disease classes. The confusion matrix and class-wise performance analysis confirmed the model's robustness and its ability to accurately distinguish between visually similar scalp conditions. These results clearly indicate that the system is reliable and suitable for real-world medical image analysis applications.

In addition to model development, this project emphasized practical usability by deploying the trained model as a web-based application. The integration of the deep learning model with a Flask-based backend and a user-friendly frontend allows users to upload scalp images and receive real-time diagnostic results. This deployment bridges the gap between theoretical model development and real-world application, making the system accessible to non-technical users. The web interface successfully displays predicted disease labels along with confidence scores, demonstrating consistent performance with offline testing results.

Overall, the proposed system offers several significant advantages over conventional diagnostic methods, including faster diagnosis, reduced human error, objective and consistent results, and improved accessibility. By enabling early detection of scalp diseases, the system has the potential to assist dermatologists in clinical decision-making and empower individuals to seek timely medical intervention. The successful implementation of this project demonstrates the effectiveness of combining artificial intelligence, image processing, and web technologies in the healthcare domain.

In conclusion, this project proves that an AI-driven approach can serve as a reliable, efficient, and scalable solution for automated scalp disease detection. The promising results obtained validate the feasibility of deploying such systems in real-world scenarios, paving the way for future advancements in intelligent healthcare applications.

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