Prateek Rohatgi, 2025, 13:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Integrating Deep Learning with Dermoscopy for Enhanced Detection of Scalp and Hair Follicle Anomalies

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Abstract-Hair fall is the common issue for many people worldwide. Almost 50% of Indian men and 20-30% of Indian women experience hair loss in any form in their lifetime. Hair loss occurs due to many factors such as aging, stress, medication, etc. Hair fall and related diseases often go unnoticed in the beginning and patients find it difficult to differentiate between hair loss and a regular hair fall. When the situation gets worsened, then they get aware of the illness. When they consult a dermatologist, then the diagnosis gets delayed. Due to the latest Deep Learning (DL) technologies and its applications, it is easy to assist Dermatologists with faster disease detection and diagnosis. In this research, 10 diseases are used for detection namely Alopecia Areata, Contact Dermatitis, Folliculitis, Head Lice, Lichen Planus, Male Pattern Baldness, Psoriasis, Seborrheic Dermatitis, Telogen Effluvium and Tinea Capitis. 12000 images are divided into 10 classes containing 1200 images in each class. Images were preprocessed by denoising, enhancement and data augmentation. Hyperparameter tuning, fine tuning and regularization was also done to make the model more precise with learning rate of 0.0001, pretrained VGG16 model and Dropout probability of 0.5. Overall training accuracy of 99% with a validation accuracy of 93% is obtained.

Keywords- : Hair fall, Hair loss, Dermatologists, Deep learning (DL) technologies, Disease detection, Diagnosis.

I. INTRODUCTION

A ubiquitous problem for a lot of people worldwide is hair fall. A large number of individuals are affected with male pattern baldness. As per research data, 80% of men above than the 70 years of age and 42% of men below 50 years of age have mild to extensive baldness [1-2]. Compared to other traditional groups, white males are found to be more susceptible for pattern baldness [3]. Finding a treatment for baldness is challenging due to involvement of many variables. Before we consider the effects of hormones and the environment, one study discovered that more than 200 hereditary components contribute to pattern balding [4]. Research indicates that Covid may intensify pattern hair loss [5]. Male pattern baldness is a complicated disease. As per literature, the baldness genes account for 79% of male baldness, which is inherited [6]. Recently many researchers suggested that treatment for baldness will be available very soon and can be cured in humans. In latest research, it is found that genes could explain why, in contrast to most mammals, humans eventually became hairless [7]. With the help of stem cell therapy, the solution of the hair loss may be achieved [8]. In the research of June 2022, the TGF-beta, a single protein, is useful for growth and destruction of follicles [9]. According to the research of 2021, hair growth improved threefold in mice after the adrenal glands were removed [10]. Researchers in 2020 remodeled the genes responsible for hair loss by utilizing Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) which is a gene editing technique [11]. Japanese researchers in 2019 publicized a technique to produce hair beads which is a kind of collagen-enriched cell aggregate made up of numerous cells of similar variety that were joined together [12]. Body's production of DHT from testosterone can be hindered by Finasteride. Notably, less DHT is getting to one's hair follicles. It doesn't harden them to the hormone [13]. Finasteride is significantly less successful than Dutasteride at promoting hair growth and functions similar to it [14]. Nizoral is a type of shampoo which include the antifungal and anti-inflammatory drug ketoconazole. Demonstration has been done to boost hair density in male pattern baldness patients [15]. Shampoos which contain caffeine can be used for the treatment of hair loss and are among the products that can successfully treat pattern baldness [16–17].

According to research, 20–30% of Indian women and over 50% of Indian men suffers from hair loss. Several causes such as aging, stress, medicine and more can cause hair loss. Rise of stress levels in patients with hair loss lowers their quality of life. Diagnosis of Alopecia Areata is the common area of hair loss. Tinea Capitis causes the patches of Alopecia which requires patches of alopecia caused by tinea capitis require extensive treatment. Alopecia nonscarring and noninflammatory, telogen effluvium is brought on by physiological or psychological stress [18].

An annoying skin condition known as contact dermatitis (CD) is often brought on by exposure to or contact with allergens [19]. An inflammatory reaction that occurs inside the superficial component of the hair follicle—which may include the follicular base or the perifollicular hair follicles—is called folliculitis. The follicle's pilosebaceous unit is split up into three compartments: the inferior segment (hair bulb and stem), the isthmus (maximum of the sebaceous duct and arrector pili protuberance) and the infundibulum (superficial section) [20].

The minute parasites which are called head lice are residing in our hair. Our scalp used to feed the blood to head lice. Many find their bites highly hideous resultant cause of itching.

Apart from that, they don't carry any infections and are mostly safe. The majority of the time, head lice deposit their eggs close to the scalp, near the hair roots. Usually, the following generation hatches in a week or so. Nits are the name for the eggs that head lice lay [21]. There is no known etiology for an inflammatory skin and mucous membrane condition known as Lichen Planus (LP). Plaques, itchy papules and violaceous are seen on wrists, lower back and ankles. Lichen Planopilaris (LPP) is the term used to describe lichen planus of the scalp and other hair-bearing regions. In areas of inflammation, little red follicular papules and macules develop, which eventually cause scarring alopecia [22].

Genetically determination of progressive process results in the progressive conversion to vellus hair from terminal hair is known as Male Pattern Baldness or Androgenetic alopecia (AGA). The age of onset and the rate of progression both vary, but the generality rises with age [23]. Erythematous plaques can be seen with long term inflammatory and proliferative skin disorder, Psoriasis, coated in silvery scales, especially on the extensor surfaces, lumbosacral area and scalp [24]. One common inflammatory skin disease that mostly affects the scalp, face and body folds is known as Seborrheic dermatitis (SD). It is found with a papulosquamous morphology in these locations. Infantile (ISD) and Adult (ASD) versions of Seborrheic Dermatitis sees the reflection of the bimodal occurrence of the disorder [25].

II. CHALLENGES AND CONTRIBUTIONS

One of the most common computer vision application is to detect diseases with the use of digital images. Researchers make the most of a pool of digital images that are obtained from many different datasets. We can preprocess and feed the images into the neural network. Then we can develop a model to detect the disease. Lamentably, to detect scalp diseases, the smallest amount of research has been performed with the machine-learning approach. There are several distinctive challenges at the back of this. The very first point is that hair diseases are not restrained and can be spread to different scalp regions. Second, every image needs to be of different types and they need separate steps of preprocessing before they are feeded to neural networks. Variety of hair colors, types and scalp skin tones around the detection zones makes the processing of images more cumbersome. Third is non availability of proper dataset for scalp diseases over the internet. Also the images taken from the internet differ in resolution and size. In addition, consciousness of correcting and minimalizing the error in disease detection is very important otherwise, the high false-negative and false positive rates result in misdiagnosis of the disease which can worsen the loss of hair.

The development of model to prevail over these challenges has helped in successful classification the Alopecia Areata, Folliculitis, Contact Dermatitis, Head Lice, Lichen Planus, Psoriasis, Seborrheic Dermatitis, Tinea Capitis, Male Pattern Baldness and Telogen Effluvium diseases with a minimum rate of false-negative and false positive rate. Though collection of images from the internet is labourous for the diseases and the images varies in resolution, shape and color, we applied various preprocessing steps, such as denoising, enhancement, resizing and created a dataset that might help in further research related to scalp diseases.

III. RELATED WORKS

In health informatics, the use of machine learning techniques for disease diagnosis is becoming more and more common. Images of affected areas can quickly identify a number of disorders related to the skin and scalp. In one study, [26] constructed a framework to distinguish between healthy hair and alopecia areata. They acquired 68 hair photos from DermNet that showed alopecia areata and 200 healthy hair images from the figaro1K collection. Three essential features—texture, shape, and color—were retrieved from the photos following a sequence of enhancement and segmentation steps. For the purpose of classification, the researchers made the use of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM), dividing the dataset into 70%-30% of train-test-split. KNN and SVM, respectively, yielded an overall accuracy of 88.9% and 91.4% when utilizing a 10-fold cross-validation strategy. It should have been highlighted that utilizing different machine learning techniques could boost the accuracy rate. Furthermore, because Histogram Equalization (HE) introduces noise into the output image, distorting the signals, applying HE for image enhancement made it more difficult to extract precise texture information from distorted images. This framework is less dependable due to the reason that study focused on only alopecia areata disease and ignored inter-class distinctions between diseases of other similar types.

Towards the possibility for concealing other diseases like alopecia areata, a different study [27] suggested a methodology for identifying alopecia early on. For this study, 100 samples were used, of which 20% served as testing data and the remaining 80% as training data. Researchers explored the four characteristics: hair follicle, degree of damage to the hair, nail brittleness, and hair length. For detection, a two-layer feed-forward network with backpropagation was employed. With four input neurons, ten hidden neurons, and a linear output neuron, the suggested model system obtained a training accuracy of 91% and a validation accuracy of 86.7%. With a gradient of 0.059687 at epoch 4, it displayed the best performance. The study does, however, have certain shortcomings because the data source was not mentioned, and the sample sizes for each data class were not differentiated. Furthermore, no pre-processing of the gathered photos was done. Without an appropriate data balancing strategy, overfitting may occur, even though it was not included in this research. Additionally, they neglected the computation of the false negative and false positive rates of the model. It is a critical aspect of a model created specially for healthcare system. A connected study [28] was conducted for the diagnosis of skin diseases, using machine learning to identify psoriasis, melanoma, and eczema by examining a digital image of the affected skin area.

Eighty photos from numerous websites those were specialized in skin conditions made up their dataset. They were able to obtain 100% accuracy in disease classification by extracting features with a convolutional neural network and then introducing multiclass support vector machines (SVM) on those features. They did not, however, investigate overfitting problems or additional crucial model performance matrices.

By using a CNN model and after feature extraction, support vector machines (SVM) was used for the purpose of classification, the authors of article which was based on skin disease based detection [29] proposed a scheme to classify the skin bruise within five categories. With the help of 10-fold cross-validation technique the accuracy was obtained as 84.21% and 9144 photos were obtained. Generally, it is seen that a few researches have been carried out on hair diseases. In recent publications [35] and [36], the datasets were found which were having false negative, false positive rates and dependability of the model were also not seen. With the use of Convolutional Neural Network technology, the accuracy, scores and precision were enhanced for pictures of hair diseases .

IV. DATA DESCRIPTIONS AND DEVICES

Data Collection

The most challenging part of using visual images for disease classification and prediction is data collection. Less appropriate images are frequently found for a particular illness. The pictures are also scattered across the internet. Several websites catering to medical professionals were among the sources of the images used in this study, including DermQuest, DermNet, MedicineNet, DermnetNZ, and Kaggle. The number of images of each type of disease is listed in Table 1. Ten classes comprise the total of 12000 images that we have of hair diseases. Each class comprises 1200 images. The dataset is made available to the public on [30].

TABLE 1. Images per Disease.

Diseases	**Number of Images**
Alopecia Areata	1200
Contact Dermatitis	1200
Folliculitis	1200
Head Lice	1200
Lichen Planus	1200
Male Pattern Baldness	1200
Psoriasis	1200
Seborrheic Dermatitis	1200
Telogen Effluvium	1200
Tinea Capitis	1200

Devices

The research was conducted on NVIDIA GeForce RTX 3060 device having running on Windows 10 Pro operating system. The device has 16 GB, 1 x 16 GB, DDR4, 3800 MHz random access memory (RAM), and 256 GB, M.2 PCIe NVMe, SSD, Class 35 (NVRAM). For the classification of images, we utilized AMD Ryzen 7 5800X 8-Core Processor.

V. PROPOSED MODEL

This section contains an introduction to our model's system workflow as well as a detailed explanation of each module's functions. As seen in Fig. 1, after an image is captured, it went through preprocessing stages and was then split into three sections: data augmentation, image enhancement, and image denoising.

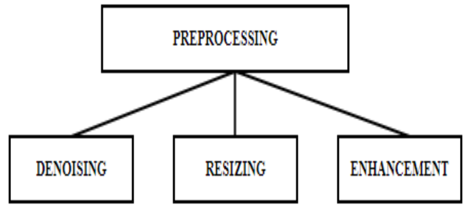

FIGURE 1. Preprocessing Techniques

The first two of these three sections were primarily focused on improving image quality, while the final section addressed model versatility. This is shown in Fig. 2. The image was given to the Neural Network model for the classification task after the preprocessing stages. In order for a convolutional neural network to successfully classify an image into ten distinct classes, we used one.

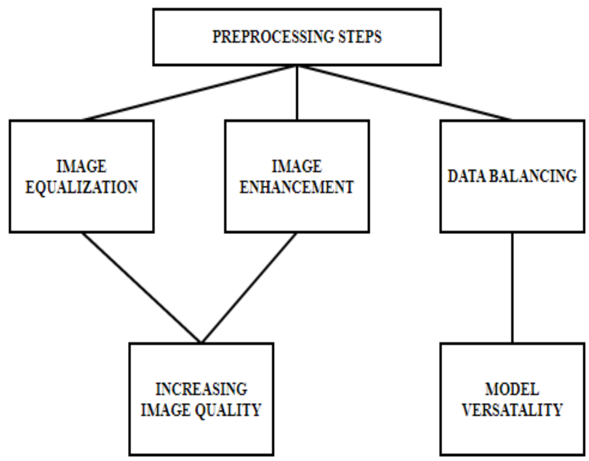

FIGURE 2. Division of preprocessing steps.

Denoising

Noise is the degradation of image signals caused by external factors [31]. Noise introduces random variations in brightness or colour information into images that have been captured. Online images are usually accompanied by some audio. Because we collected most of the data samples from different dermatology websites, our dataset's noise was not evenly distributed, which has increased its complexity. To lessen noise, we consequently applied additional filters to the acquired images. We started with the median filter in order to enhance the image classification process. The photos became blurry after applying the median filter. Figure 3 shows original and denoised image.

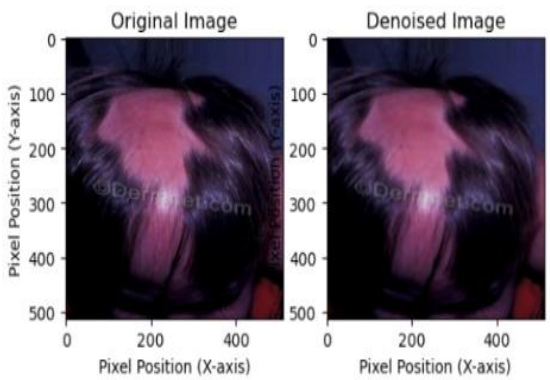

FIGURE 3. Original and Denoised Image.

A. Enhancement

Since captured images often fail to capture the natural view, contrast enhancement is often used to achieve a realistic view [32]. For a more realistic view, normalisation is required, particularly in images that have high colour depth following denoising effects [33]. The first method was called histogram equalisation, or HE. Nevertheless, because the histogram was not confined to the image's immediate vicinity, the HE lost information and increased the contrast of the background in low colour depth images. To solve the problem, we divided an image into equal-sized, non-overlapping sections and then created a histogram for each region using CLAHE (Contrast Limited Adaptive Histogram Equalisation). We distributed the clipped value over the histogram equalisation after the histogram was clipped. This allowed us to control the overamplification of contrast and create the final image that can be seen in Fig. 4.

FIGURE 4. Enhanced Images.

Data Augmentation

A deep learning model's overall performance depends on data augmentation because it makes minority class detection easier. An augmented dataset is less likely to exhibit a majority skew. Because alopecia is a common condition, we had more images of it than other diseases, which throws off the balance of the dataset for our model. In order to balance the dataset, we oversampled the infrequent class and used data augmentation techniques (re-scaling, random rotating, cropping, and vertical and horizontal flipping).

FIGURE 5. Augmented Images.

Neural Network Model

Neural Network is the most popular model for analyzing visual data. Neural networks are capable of identifying non-linear relationships between input and output with little or no human assistance. Neural networks are widely used in a variety of applications, from global or local scale modeling [34] to diagnosis through medical image classification. Neural networks are also used in automated virtual agents, call center assistance, facial recognition, image labeling, and precise video subtitles. Artificial Neural Networks (ANN), Convolution Neural Networks (CNN), and Recurrent Neural Networks (RNN) are the three types of neural networks that are currently available. Fig. 6 shows the neural network model.

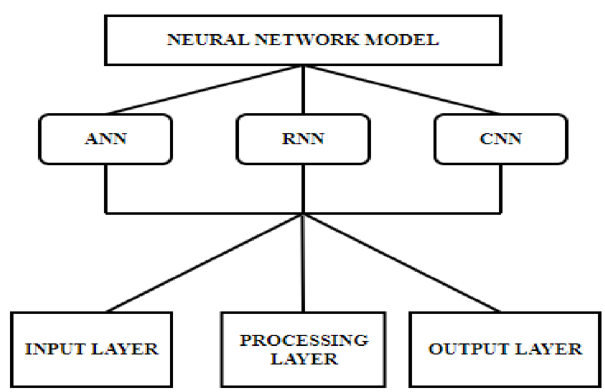

FIGURE 6. Neural Network Model.

An input layer, a processing layer, and an output layer are the three main parts of any neural network. CNN was used in this research for classification because it trains a model on the raw pixel data of an image and automatically extracts features for improved detection. To identify the ideal model for this issue, Conv2D layer and Dense Layer was employed. Following 10 iterations, we ultimately opted for a final model consisting of 3 Conv2D layer of filter size 32 and 1 Conv2D layer of filter size 128. Dense layer had 256 units and a ReLU activation function. It served as a hidden layer for learning higher-level features.

Batch size of 32 with 50 epochs were used in order to train the model. For the purposes of training and validation, the preprocessed data was split into a 80-20 train-test split. 3 x 3 square kernel, 10 output units, 4608 inputs, and a softmax output made up our model. In order to investigate the non-linear relationship between input and output variables and to stop the exponential growth of necessary computation, ReLU as an activation function was chosen. To shrink the size of the features map, input passed through a pooling layer with a 2 x 2 kernel size after each convolutional layer. When moving from the pooled features map to the fully connected layer, all of the resulting 2-D arrays went through the flatten layer and were transformed into single-dimensional long continuous linear vectors. Each and every output pixel from the convolutional layers was linked to three output classes in the fully connected layer. Despite the high computational cost of dense layers, we employed two of them for our classification task. Ultimately, the three fully connected layer units were converted using the softmax activation function into a probability distribution represented by a vector of three elements, with the highest probability element being chosen as the final class. Adam optimizer was used to change the weights and learning rates in order to reduce the overall loss and improve the model's performance on the given task. Figure 7 shows the complete process of the hair disease detection.

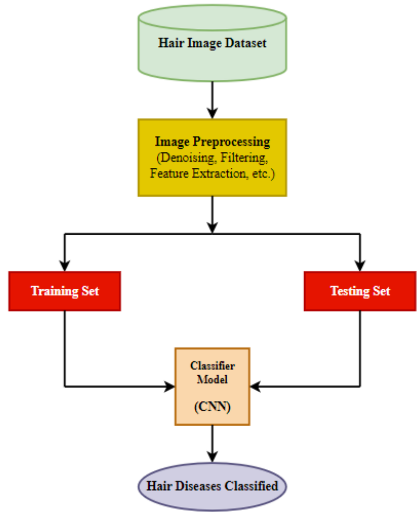

FIGURE 7. Flowchart of Hair Disease Detection

VI. RESULTS

The ideal hyperparameters as mentioned in Table 2 were used to train the CNN model.

The ideal hyperparameters used to train the CNN model.

TABLE 2. Hyperparameters of CN Model.

Hyperparameters	Values
Batch size	32
Epoch	50
Kernel Size	3 x 3
Optimizer	Adam
Pooling Size	2 x 2
Activation Function	ReLU

The dataset was split into a 80%–20% train-test split, with 1200 randomly selected images used for testing and 9600 randomly selected images used for training. Following the preprocessing steps, we trained the CNN model on the training dataset and then used the model to assess the test dataset. Fig. 8 displays the validation and training losses for each epoch. From epoch 1 to epoch 50, the training losses dropped from 1.8552 to 0.0260 and the validation losses from 1.6856 to 0.3517

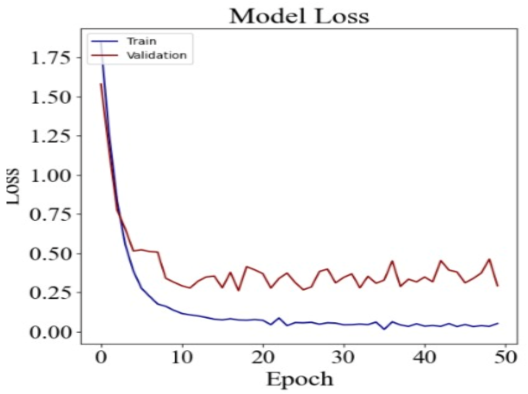

FIGURE 8. Validation and Training Loss

On the unknown data, our system obtained 93% validation accuracy and 99% training accuracy. According to Fig. 9, training accuracy and validation accuracy rose to 99% and

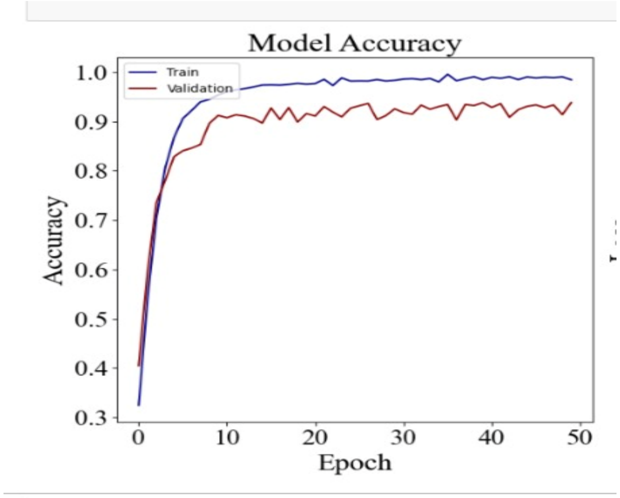

FIGURE 9. Validation and Training Accuracy.

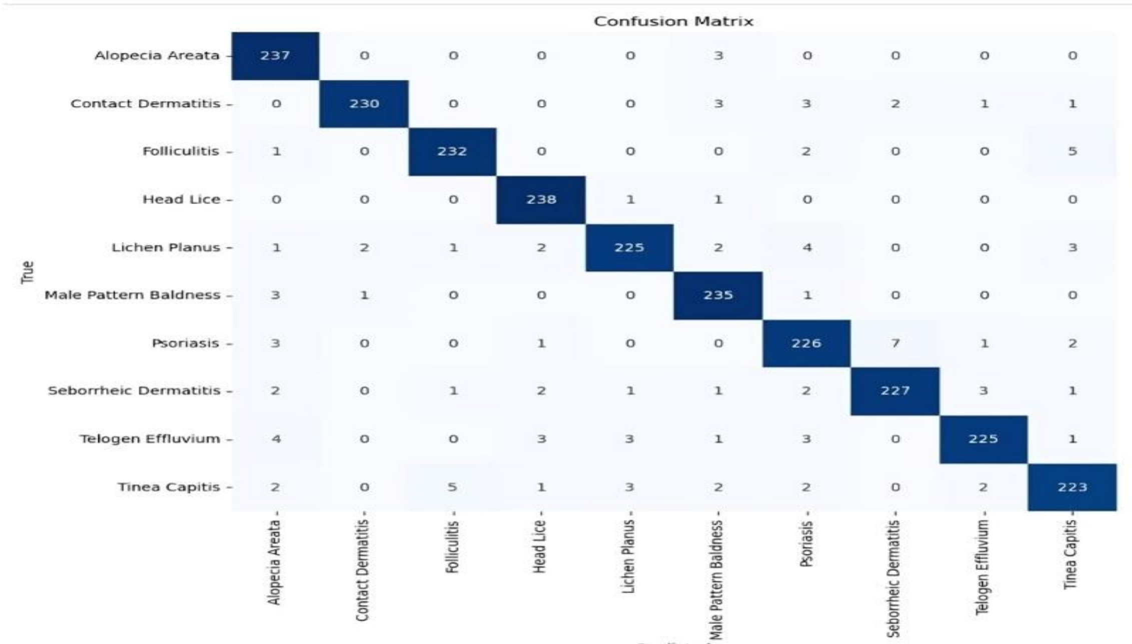

FIGURE 10. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
Alopecia Areata	0.94	0.99	0.96	240
Contact Dermatitis	0.99	0.96	0.97	240
Folliculitis	0.97	0.97	0.97	240
Head Lice	0.96	0.99	0.98	240
Lichen Planus	0.97	0.94	0.95	240
Male Pattern Baldness	0.95	0.98	0.96	240
Psoriasis	0.93	0.94	0.94	240
Seborrheic Dermatitis	0.96	0.95	0.95	240
Telogen Effluvium	0.97	0.94	0.95	240
Tinea Capitis	0.94	0.93	0.94	240
accuracy			0.96	2400
macro avg	0.96	0.96	0.96	2400
weighted avg	0.96	0.96	0.96	2400

FIGURE 11. Classification Report

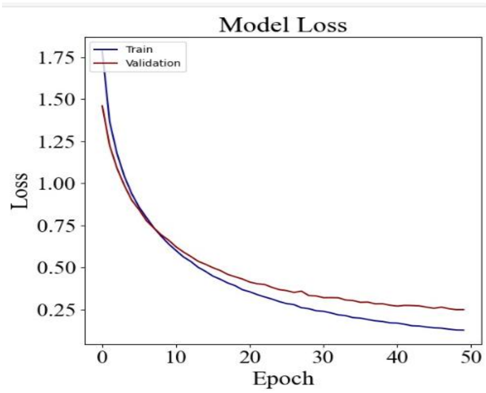

FIGURE 12. Validation and Training Loss

According to Fig. 13, training accuracy and validation accuracy rose to 97% and 93%, respectively, between epochs 1 and 50. Figure 14 shows the confusion matrix of the results produced. Figure 15 shows the classification report of the diseases predicted where it is showing Precision, Recall, F1 score, support and accuracy.

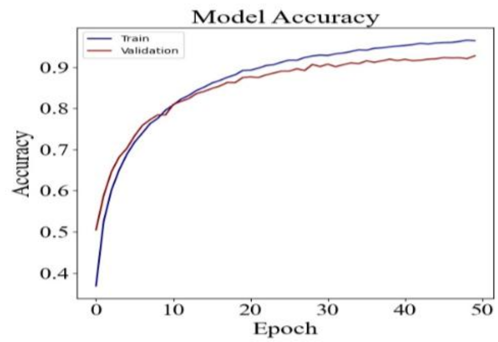

FIGURE 13. Validation and Training Accuracy

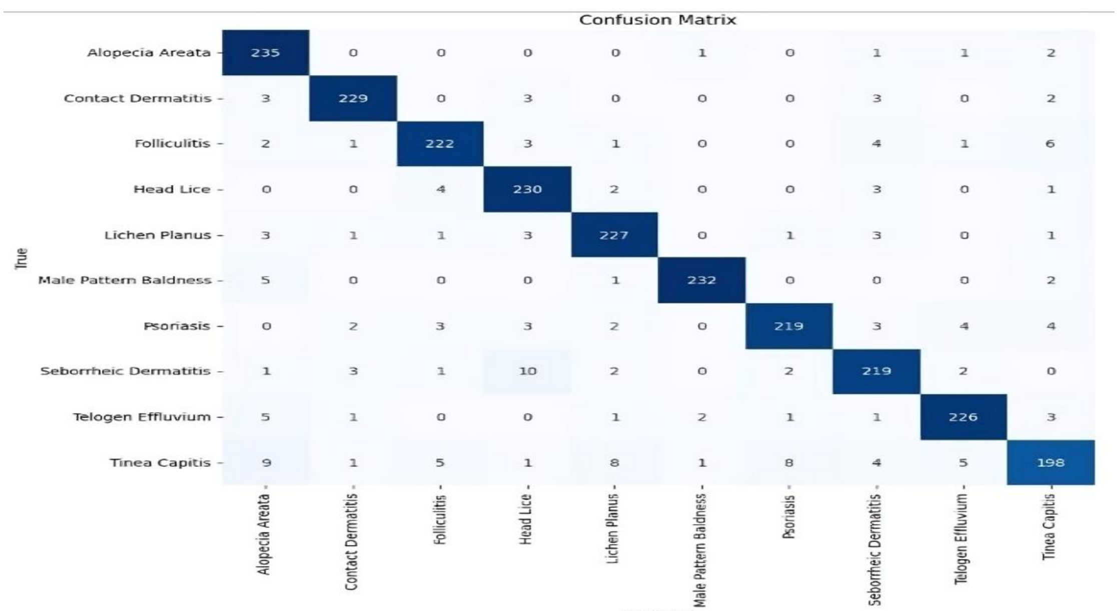

FIGURE 14. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
Alopecia Areata	0.89	0.98	0.93	240
Contact Dermatitis	0.96	0.95	0.96	240
Folliculitis	0.94	0.93	0.93	240
Head Lice	0.91	0.96	0.93	240
Lichen Planus	0.93	0.95	0.94	240
Male Pattern Baldness	0.98	0.97	0.97	240
Psoriasis	0.95	0.91	0.93	240
Seborrheic Dermatitis	0.91	0.91	0.91	240
Telogen Effluvium	0.95	0.94	0.94	240
Tinea Capitis	0.90	0.82	0.86	240
accuracy			0.93	2400
macro avg	0.93	0.93	0.93	2400
weighted avg	0.93	0.93	0.93	2400

FIGURE 15. Classification Report

However, after these results, the epochs were increased to 100. Fig. 16 displays the validation and training losses for each epoch. From epoch 1 to epoch 100, the training losses dropped from 1.7881 to 0.0421 and the validation losses from 1.4675 to 0.2284.

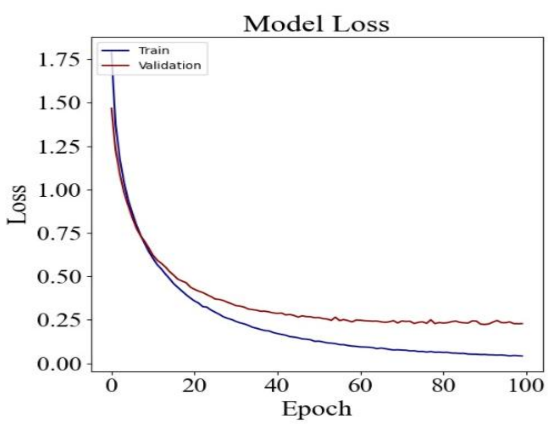

FIGURE 16. Validation and Training Loss

According to Fig. 17, training accuracy and validation accuracy rose to 99% and 93%, respectively, between epochs 1 and 100. Figure 18 shows the confusion matrix of the results produced. Figure 19 shows the classification report of the diseases predicted where it is showing Precision, Recall, F1 score, support and accuracy.

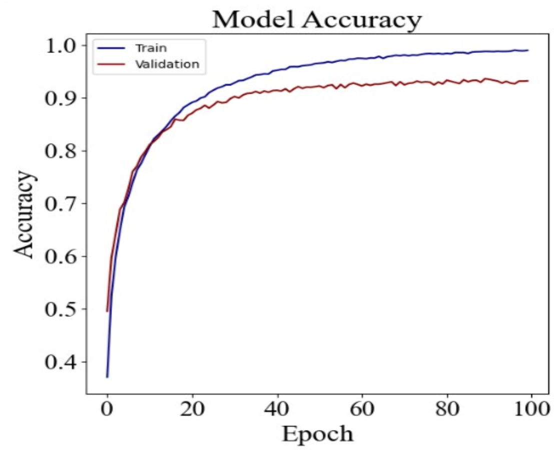

FIGURE 17. Validation and Training Loss

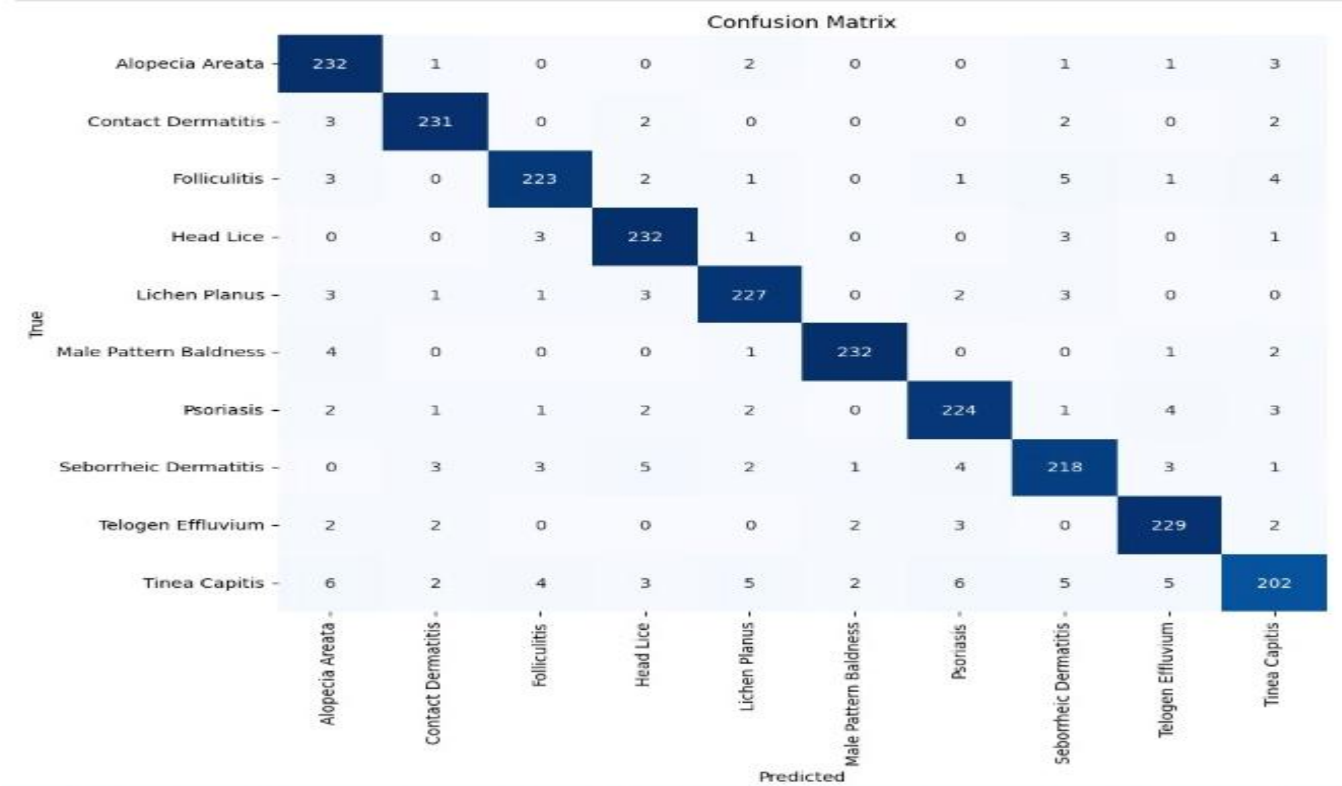

FIGURE 18. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
Alopecia Areata	0.91	0.97	0.94	240
Contact Dermatitis	0.96	0.96	0.96	240
Folliculitis	0.95	0.93	0.94	240
Head Lice	0.93	0.97	0.95	240
Lichen Planus	0.94	0.95	0.94	240
Male Pattern Baldness	0.98	0.97	0.97	240
Psoriasis	0.93	0.93	0.93	240
Seborrheic Dermatitis	0.92	0.91	0.91	240
Telogen Effluvium	0.94	0.95	0.95	240
Tinea Capitis	0.92	0.84	0.88	240
accuracy			0.94	2400
macro avg	0.94	0.94	0.94	2400
weighted avg	0.94	0.94	0.94	2400

FIGURE 19. Classification Report

VII. CONCLUSION

Due to the lack of awareness and drawn-out diagnosis tests, hair loss and scalp diseases can frequently go undiagnosed, despite the fact that early detection is crucial to the treatment process. Early disease detection could be made easier with the help of an AI-based application. In this study, we fed 12000 preprocessed image data into a 2-D convolutional neural network model to create a deep learning model that can accurately predict 10 diseases related to the hair and scalp: alopecia areata, contact dermatitis, folliculitis, head lice, lichen planus, male pattern baldness, psoriasis, seborrheic dermatitis, telogen effluvium and tinea capitis. We examined the remaining 20% of the photos to test our model after using 80% of the data to train it. Following additional training, the model yields an overall 99% training accuracy on the training data and 93% validation accuracy for the test data. With the help of our suggested system, patients and dermatologists would be better able to diagnose and treat the 10 most common hair and scalp diseases at an early stage.

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