DEEP LEARNING APPROACH FOR HAIR LOSS DETECTION: XCEPTION

Shubh Ashish, CSE Data Science, Sharda University(2021504331.shubh@ug.sharda.ac.in),

Garvit Sharma, CSE Data Science, Sharda University(2021002636.garvit@ug.sharda.ac.in),

Jyotsna Seth, Department of Computer Science, Sharda University(jyotsna.seth@sharda.ac.in)

ABSTRACT

Millions of individuals worldwide suffer with hair loss, which is a common and frequently distressing condition. Presently, dermatologists rely on visual assessments and subjective judgements to diagnose and classify hair loss. We present a novel approach to hair loss stage classification using facial pictures and machine learning algorithms in this research. We gathered a collection of facial photographs of people in various stages of hair loss and used computer vision algorithms to extract significant information from the images. We trained and evaluated a classification model using the Xception CNN model, a lightweight architecture that can be implemented on mobile devices. Our model attained an accuracy of roughly 76%, indicating the potential of face pictures and machine learning for the categorization of hair loss phases. Further research is required to improve the model's performance and confirm its therapeutic value.

INTRODUCTION

Hair loss affects an estimated 50 million men and 30 million women in the United States alone. Androgenetic alopecia is the most prevalent kind of hair loss, affecting up to 70% of men and 40% of women. It is caused by the hormone dihydrotestosterone (DHT), which reduces hair follicles and shortens the anagen (growth) phase of the hair cycle. Infected hair follicles generate shorter, thinner hair until they cease generating hair completely.

The Hamilton-Norwood classification system, which outlines seven phases of hair loss in males, is frequently used to assess the severity of androgenic alopecia. This approach is extensively utilised in clinical practise and research since it is based on the pattern and degree of hair loss on the scalp. The Hamilton-Norwood table can be modified to account for variances in hair loss patterns in women. These types are-

- Stage 1: No hair loss - This stage is characterised by no visible hair loss, with a full head of hair on the scalp.
- Stage 2: Minimal hair loss - This stage involves slight recession of the hairline at the temples, with minimal hair loss on the crown of the head. This stage is also known as the "mature hairline" stage.
- Stages 3-5: Moderate hair loss - These stages are characterised by increasing degrees of baldness, with more apparent hair loss in the crown, temples, and vertex (top of the head).
- Stages 6-7: Severe hair loss - These stages are characterised by severe baldness and a lack of hair on the scalp.

Visual judgements of hair loss are subjective and may differ amongst dermatologists. Automatic hair loss categorization approaches based on face pictures and machine learning techniques have shown promise in increasing the accuracy and consistency of hair loss diagnosis.

It is worth noting that the treatment of androgenic alopecia differs depending on the stage of severity. At Stage 2, for example, it is advised that pharmaceuticals be taken to slow the progression of hair loss. Hair transplantation surgery or wearing a wig are often mentioned options for Stages 5 to 7.

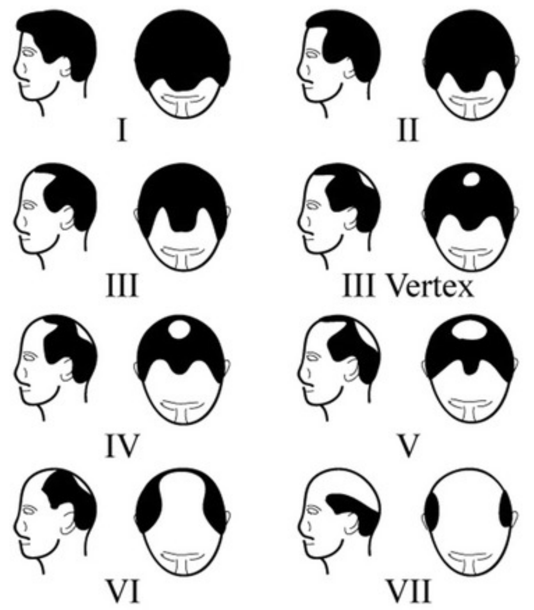


Fig1. Hamilton Norwood Scale for classifying the stage of hair loss

A binary classification model can be developed with a simple deep learning model that could predict if a person is affected by androgenic alopecia(or not). Deep-learning based analysis can be done on patients in day-to-day life and classifying them into 4 stages derived from the hamilton norwood table as per the severity of androgenic alopecia.

Apart from the treatment there can be many other applications of pattern baldness detection. Some of the categorised applications are.

i) Screening: Automatic hair loss detection methods can be utilised in public health settings, such as community health fairs or screenings, to screen for hair loss in large populations. This can aid in identifying individuals who may require additional examination or therapy.

ii) Occupational Health: Hair loss detection and categorization technologies can be employed in industries where hair loss may affect work performance or safety, such as the military or aviation. Companies can use these technologies to monitor employees' hair loss and take necessary precautions, such as providing protective equipment or accommodations.

iii) Insurance: Insurance firms can utilise hair loss detection and categorization techniques to estimate the risk of hair loss and make coverage or premium choices. This can assist insurance firms in more properly evaluating risk and making more informed coverage selections.

iv) Personalised marketing: Businesses that provide hair products or treatments can utilise hair loss detection and categorization algorithms to create tailored marketing campaigns for individuals depending on their hair loss stage. This can help businesses reach out to potential consumers more efficiently and supply them with products or services that are tailored to their individual requirements.

The major goal of this study is to provide a unique method for identifying hair loss phases using face photographs. The suggested method seeks to provide an accurate and user-friendly tool for early identification and monitoring of hair loss, which can help doctors plan suitable therapies and people with their own hair care regimen.

Conventional hair loss categorization methods rely on clinical examination and scalp biopsies, which may be intrusive, time-consuming, and costly. Our methodology uses face photographs to give a non-invasive and convenient method for hair loss categorization that may be easily used in clinical and research contexts. Face photographs are simple to obtain and may be obtained utilising ubiquitous digital devices such as cellphones or webcams.
Furthermore, our methodology aims to improve the accuracy of hair loss categorization by utilising current advances in computer vision and machine learning, while keeping in mind the constraints of resources such as a smartphone. We intend to construct a sufficiently accurate and robust model for hair loss classification that can be readily deployed on a smartphone by training a lightweight deep neural network on a restricted dataset of facial photos.

APPLIED METHODOLOGIES

There are various potential approaches for classifying hair loss using face photos. Convolutional neural networks (CNNs), a form of deep learning model well-suited for image classification tasks, are one intriguing technique. Transfer learning, which includes adapting a pre-trained neural network to a new task with insufficient data, might also be effective. Another approach that might be used to produce synthetic versions of facial photos and expand the total size and variety of the dataset is data augmentation.
In this article, we used the Xception convolutional neural network architecture to classify hair loss in face photographs. Xception is a robust deep learning model that was trained on the large-scale ImageNet dataset, making it ideal for transferring learning to new applications with less data. We were able to obtain excellent accuracy by fine-tuning the Xception model on our hair loss categorization challenge and using its capacity to learn spatial and channel-wise data separately. Overall, the effectiveness of our hair loss categorization model was aided by the adoption of the Xception architecture and transfer learning technique.

ImageNet is a large-scale image identification competition that was launched in 2010. It has over 14 million photos in over 20,000 categories, making it one of the largest image datasets accessible for deep learning model training. The photos in ImageNet are largely natural images of objects, animals, and settings, with photographs of people and their faces accounting for a sizable fraction of the dataset.

Fig 2. Image-Net dataset

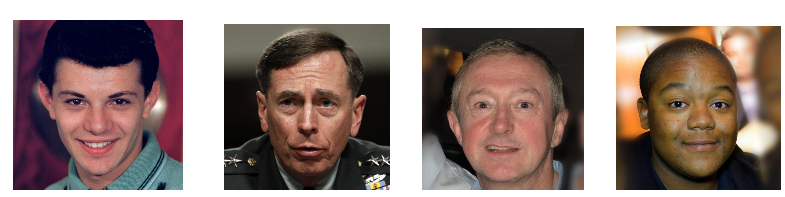
The pre-trained Xception model on ImageNet is utilised as the starting point for fine-tuning on the hair loss classification job in our scenario of hair loss classification using face photos.
We added two hidden layers and one output layer to the network to fine-tune the pre-trained Xception model on the hair loss categorization job. The hidden layers were made up of fully linked layers with LeakReLU activation functions, enabling the model to learn nonlinear representations of the input data.
We also used regularisation techniques like L2 weight regularisation and dropout to avoid the model from overfitting.

EXPERIMENTAL STUDY

A. Dataset Preparation

We used the CelebA dataset for this work, which is a popular dataset for face attribute identification. The collection includes over 200,000 celebrity photos annotated with variables such as gender, age, and hair colour.
We used 1,000 photos from the CelebA dataset that were labelled with hair loss phases according to the Hamilton-Norwood scale to train and assess our hair loss classification algorithm. We picked 250 photos from each of the four hair loss stages: none, early stage, moderate stage, and advanced stage.
We randomly divided the photos into two groups: training and testing. The training set has 800 photographs (200 from each category), whereas the testing set had 200 images (50 from each category).

Filtering of Stages- The dataset under research includes photos labelled as bald or not bald, with bald images accounting for just 2% of the whole sample. We used the Hamilton-Norwood categorization system for male pattern baldness to enhance the current labelling and generated four additional classifications based on it.



Stage 1 Stage 2 Stage 3 Stage 4

Fig 3. Figure showing various hair loss stages

Class 1 on the Hamilton-Norwood table corresponds to type 1, which has a modest recession of the hairline at the temples. Class 2 includes types 2, 3, and 4, which have varying degrees of hair loss in the crown and/or frontal parts of the scalp. Class 3 includes types 5, 6, and 7, which represent advanced stages of hair loss with considerable balding of the head and/or frontal areas. Class 4 is a new group of bald people not included in the Hamilton-Norwood table, comprising those who have hair loss from sources other than male pattern baldness.

We later filled the data manually 250 across each category and then split it into 80 to 20 ratio for training and testing i.e. 800 images for training the model and 200 for testing. There might be some noise or deformities in the images which can hamper the accuracy of the model so we avoided such images and trained the model with best possible images.

Fig 4. Various deformities in the dataset

Data Augmentation- To increase the training size we introduced data augmentation for each image in the training set. We applied i) gaussian blur ii)gaussian noise iii) horizontal flip iv) CLAHE. A figure below is demonstrating the applied data augmentation techniques on a sample image.

Fig 4.Figure demonstrating various data augmentation techniques i)Horizontal Flip ii)Gaussian Noise iii)Gaussian Blur iv)CLAHE

We used data augmentation techniques on the current dataset to test the performance of our models. Based on the Hamilton-Norwood categorization scheme for male pattern baldness, we classified the dataset into four groups, each indicating a different stage of hair loss.

We performed three approaches to each image in the dataset for the first category of data augmentation: horizontal flip, Gaussian blur, and Gaussian noise. This resulted in 800 photos each class and 3200 total photographs. These augmented photos were used to train and test our models, and their performance on the test set was assessed.

We performed four approaches to each image in the dataset for the second category of data augmentation: horizontal flip, Gaussian blur, Gaussian noise, and Contrast Limited Adaptive Histogram Equalisation (CLAHE). This resulted in 1000 photographs each class and a total of 4000 images. We trained and tested our models on these augmented photos and compared their performance to models trained on the first category of augmented images.

IMAGE PREPROCESSING -To improve the deep learning model's performance and accuracy, we adopted a popular picture preprocessing technology that is commonly used to boost the variety and resilience of the training dataset.

The Image module from the Pillow library was used to scale the pictures to a standard size of 224x224 pixels as the first stage in the image preparation pipeline. This was done to guarantee that all photographs were the same size, which is required for the Xception model to function correctly. The pixel values of the photos were then normalised using the Xception model's preprocess_input function. This function adjusts pixel values to a range suited for the Xception model, which requires input data in the -1 to 1 range.

We estimated the average accuracy across each dataset to assess the model's performance on these datasets. Table 1 shows the results of this study, which show that the augmentation strategies utilised in datasets 1 and 2 resulted in a considerable increase in accuracy, with an average improvement of around 14%. This is a significant increase that demonstrates the utility of data augmentation strategies in improving model correctness.

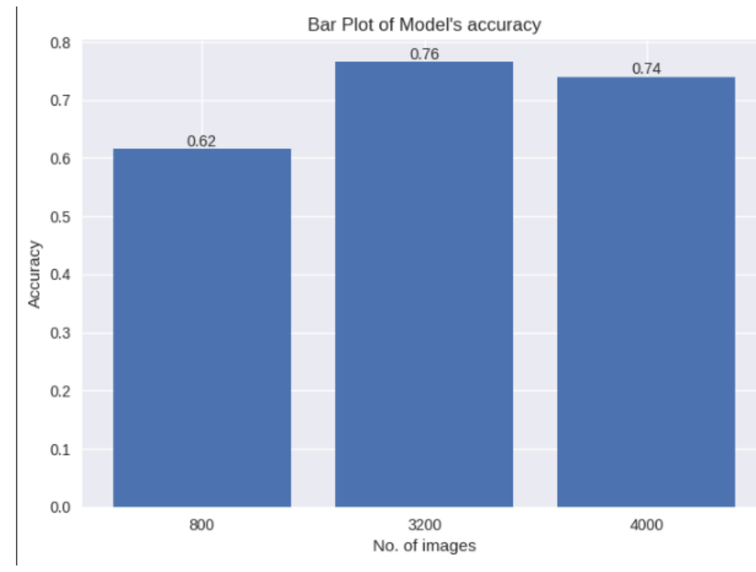


Fig 5. Barplot for comparison of datasets i)basis-800 images ii) data augmentation-3200 images iii) data augmentation -4000 images

Our findings show that using data augmentation approaches may greatly increase the accuracy of deep learning models, especially when dealing with datasets that are small or diverse.

Model	Basis	Augmentation1	Augmentation2
Accuracy	61.5	76.4	74.0

Table 1: Comparison of average accuracies obtained on the test set classification

While data augmentation techniques may be extremely helpful in improving the accuracy of deep learning models, it is crucial to emphasise that increasing the quantity of augmented pictures does not always result in improved model performance. In fact, the inclusion of too many enhanced photos may result in a loss in accuracy.

CONCLUSION

To solve the issue of hair loss classification, we used deep learning techniques on face photos and created an image-based hair loss classification system based on the Hamilton-Norwood scale. We manually annotated a dataset of facial photographs and artificially supplemented it with different label-preserving treatments to prevent overfitting. Using the Xception model, a lightweight convolutional neural network, we demonstrated the ability to reliably predict hair loss from face photos captured using mobile phones.

FUTURE WORK

To improve our model's performance, we intend to investigate transfer learning approaches using pre-trained models created exclusively for face recognition, such as dex-imdbwiki and dex-chaLearn. We want to increase the accuracy and robustness of our algorithm in identifying hair loss by using the knowledge gained from these large-scale datasets.