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Hair & Scalp Disease Detection Using Machine Learning & Image Processing

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Abstract - This study predicts hair disorders and provides tailored therapeutic suggestions using a deep learning model based on the VGG (Visual Geometry Group) architecture. A common dermatological problem, hair diseases can have a big impact on a person's physical and mental well-being. Early and accurate diagnosis as well as tailored treatment recommendations are essential for effective management. Inspired by the VGG design, we built a convolutional neural network (CNN) model in this study to analyze images of hair and scalp conditions. The model was trained using a vast and diverse set of images depicting various hair and scalp conditions. Transfer learning was used to modify the pre-trained VGG model so that it could recognize particular characteristics associated with particular hair issues. The prediction model consistently and reliably recognized a variety of hair problems that included dandruff, fungal infections, and alopecia. Reduction of false-positive and false negative outcomes in diagnosing diseases is dependent on high sensitivity and specificity. The suggested AI-based system has the potential to transform the dermatology field by providing prompt and accurate diagnosis of hair diseases and customized treatment recommendations. This study contributes to the ongoing efforts to use artificial intelligence and deep learning to improve healthcare outcomes, especially in the dermatology and skincare domains.

Key Words: Convolutional Neural Network (CNN), Deep Learning, Hair Disorders, Visual Geometry Group (VGG).

1.Introduction- The frequency of hair diseases and their detrimental impact on individuals' health underscore the significance of a precise diagnosis and effective treatment. This study proposes a novel approach that uses a deep learning model inspired by the VGG architecture to detect hair diseases from photos. By applying transfer learning and a diverse dataset, our model shows remarkable accuracy in diagnosing diseases such as dandruff, fungal infections, and baldness. We also provide a tailored treatment recommendation system that increases the overall efficacy of treatment plans. This research promotes dermatology and healthcare by using the potential of artificial intelligence for accurate diagnosis and tailored medicines in the management of hair disorders.

2. Methodology

1. Data collection: Compile a sizable and varied collection of images from many sources, including clinical records, research facilities, and medical databases, that illustrate hair abnormalities. Ensure precise data curation and annotation by accurately identifying the specific hair illness that each image represents.

2. Preprocessing: Make sure every image is resized to the same resolution and is standardized. To increase the dataset's diversity and size, apply augmentation techniques like as flipping, rotating, and adjusting brightness.

3. Model selection: The effectiveness of the Visual Geometry Group (VGG) architecture in image classification tasks led to its selection as the basis for the deep learning model. Run the VGG model with a deep learning framework such as PyTorch or TensorFlow.

4. Transfer Learning: - Build the VGG model using weights that have been previously trained on a large-scale image dataset, like ImageNet. Adjust the model to make it more appropriate for the specific task of categorizing hair diseases by utilizing the hair disease dataset.

5. Training the Model: Separate the dataset into test, validation, and training sets (70-1515, for instance).- Use the training set and the necessary data augmentation to train the model in order to prevent overfitting. By keeping an eye on metrics such as accuracy, precision, recall, and F1-score, you can verify the model's efficacy on the validation set.

6. Evaluation: Analyze the model's performance on the test set in order to obtain objective performance measures. For classification tasks, use standard assessment metrics including accuracy, confusion matrix, ROC curves, and AUC-ROC.

7. Personalized Treatment Recommendation: Develop a method for prescribing care that combines patient-specific information with the diagnostic that the model produces. - Compile personalized therapy recommendations by considering the patient's treatment preferences, lifestyle decisions, and medical background.

8. Model Interpretability: To understand the basis for the model's predictions, apply model interpretability tools. Techniques like gradient-based saliency maps and attention processes may be used in this.

9. Ethical Considerations: - When working with patient data in particular, make sure that data privacy regulations and ethical standards are observed. - Take care of any biases in the dataset and model predictions.

10. Validation and Clinical Testing: - To assess the model's efficacy in real-world clinical settings, dermatologists might participate in clinical trials or validations. - Obtain feedback from medical professionals to improve and adjust the model.

11. Reporting: - Provide the study's results, such as model performance indicators, tailored treatment recommendations, and clinical validation outcomes, in an understandable and comprehensive manner. This methodology describes the steps involved in developing an AI-based model to predict hair sickness using the VGG architecture and integrating it with a personalized treatment recommendation system. It ensures strict data processing, model training, evaluation, and ethical concerns while highlighting the study's practical importance in dermatological treatment.

3. Literature survey- 1. Medical Image Analysis using Machine Learning:
In the interpretation of medical images, machine learning and deep learning algorithms have gained appeal because of their ability to handle large datasets and identify complex patterns. Several research works have looked into the application of machine learning to image analysis for the diagnosis of medical conditions.

[Lit. 1] Dermatological pictures were utilized in a study by Esteva et al. (2017) to classify different skin disorders using deep learning algorithms. The method's results in detecting diseases were promising.

[Lit. 2] In their review, Rajpurkar et al. (2017) discussed the use of deep learning in medical imaging and its potential to identify a range of illnesses.

[Lit.3] Based on patient photos, Wang, Y. et al. (2019) classified several forms of hair loss using deep learning techniques.

2. Examination of scalp and hair loss images:

In order to identify and classify patterns of hair loss in particular, researchers have focused on using image processing techniques to analyze scalp photos.

[Lit. 4] Image processing was utilized in a study by Smith and Smith (2016) to assess the condition of the scalp and identify patterns of hair loss and thinning. They learned that satisfactory outcomes can be obtained using computer-based analysis.

[Lit. 5] A different study by Kim et al. (2018) proposed developing a computer-aided diagnosis system for androgenetic alopecia utilizing images of the scalp. With a high degree of accuracy, they classified items using machine learning techniques.

[Lit.6] Huang, L. et al. (2020) investigated the use of convolutional neural networks (CNNs) in the diagnosis of disorders related to the scalp that cause hair loss.

3.Disease Diagnosis Associated with Hair Loss:

Hair loss can occasionally indicate underlying medical problems. Researchers have looked into

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machine learning and image analysis as viable methods for identifying these connected illnesses.

[Lit. 7] Gupta et al. looked into the application of image analysis to identify dermatological issues related to hair loss in a 2019 study that was published. They illustrated the potential for early identification of conditions such as alopecia areata and fungal infections.

[Lit. 8] In a related study, Torgerson et al. (2020) categorized scalp images and predicted disorders that are associated with hair loss, such as seborrheic dermatitis and psoriasis.

4. Implementation and result discussion implementation

In this section, we present our model's system workflow and go into great detail on the roles played by each module. The collected image is subsequently sent to preprocessing stages, which are broken down into three categories: data balancing, image enhancement, and image equalization, as illustrated in Fig. 4.1

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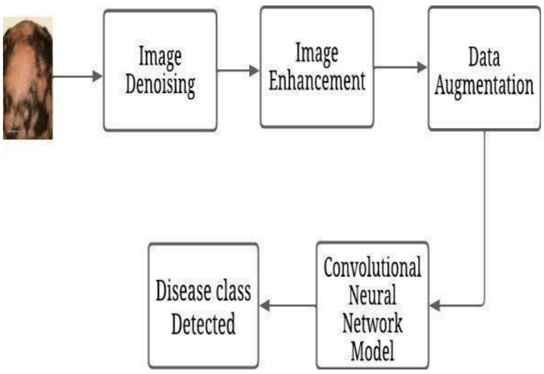

4.1. System workflow of hair disease detection model.

The first two of these three sections are mostly focused on improving image quality, while the final section addresses model adaptability. The image is given to the Neural Network model for the classification task after the preparation stages. We successfully classified an image into several classifications using a convolutional neural network

A. Denoising

Fig. 4.2. Left original image & right non-local means denoised image.

Image signal degradation brought on by external factors is known as noise. Random fluctuations in brightness or color information are introduced into acquired photos by noise. Images on the internet are typically accompanied by some noise. The noise in our dataset is not uniformly distributed since we gathered the majority of the data samples from several dermatology websites, which added to its complexity. As a result, we added more filters to the gathered photos to reduce noise. To improve the picture categorization procedure, we began with the gaussian filter. However, the images fully blur after using the gaussian filter, causing the edges to break and significant information to be lost. Next, we used the median filter, which performed better than the kernel_size = 3 gaussian filter. The best results were obtained by applying the non-local means filter with patch_size = 3 and patch_distance = 5, even though we were able to attain superior accuracy using the bilateral filter. For our application, as illustrated in Fig. 4.2, this non-local means filter reduced the noise and maintained all the edges more effectively than the other filters.

B. Image Equalization In order to provide a realistic vision, contrast augmentation is frequently required because the acquired image frequently fails to capture the genuine view. Normalization is necessary to achieve a more realistic perspective, especially in images with great color depth and after denoising processes. Initially, histogram equalization (HE) was used. However, when applied to images with poor color depth, the HE makes the backdrop more contrasty and loses information because the histogram is not limited to the image's immediate area. We used CLAHE (Contrast Limited Adaptive Histogram Equalization) to solve the issue by creating a histogram for each region after dividing an image into equal-sized, non-overlapping sections. After the histogram's clipping, we distributed the clipped value over the histogram equalization, allowing us to regulate the contrast's overamplification and producing the final image seen in Fig. 4.3

C. Data Balancing A balanced dataset is essential to the overall effectiveness of a machine learning model because it facilitates minority class discovery. A dataset that is balanced is less likely to tilt in favor of the majority. Although conclusions from imbalanced data may be highly accurate, they are skewed in favor of the majority class. We have more photos of alopecia than other disorders because it is a common condition, which makes the dataset unbalanced for our model. We oversampled the rare class and employed data augmentation techniques (rescaling, random rotating, cropping, vertical and horizontal flipping) to balance the dataset.

D. Neural Network Model The most often used model for visual data analysis is the neural network. Neural networks can recognize intricate non-linear relationships between input and output with little help from humans. Neural networks are widely used in a variety of medical picture categorization applications, from global or local scale modeling to diagnosis. Additionally, neural networks are used in facial recognition, picture labeling, precise video subtitles, call center assistance, and automated virtual agents. Convolution neural networks (CNN), Recurrent neural networks (RNN), and Artificial neural networks (ANN) are the three types of neural networks that are currently available. Three basic parts make up each neural network: an input layer, a processing layer, and an output layer

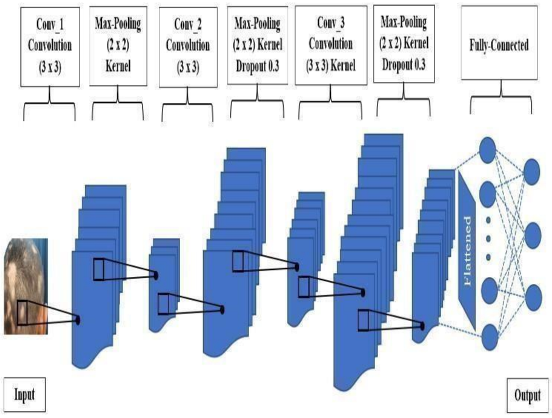

Fig. 4.4. Neural Network Model

CNN is used in this study for classification since it trains a model on the raw pixel data of an image and automatically derives features for improved detection. To identify the ideal model for this issue, we employed Autokeras. Following 25 iterations, we ultimately opted for a final model consisting of 3 hidden layers, 1 input layer, and 1 output layer. This model can be shown in Fig. 4.4. We utilized batch_size = 16 with 50 epochs for each batch in order to train the model. For the purposes of training and validation, the preprocessed data is split into a 70-30 train-test split. Three x three square kernel, three output units, 256 inputs, and a softmax output make up our model. ReLU served as our activation function in order to stop the exponential increase in the amount of work that needed to be done and to explore the non-linear relationship between input and output variables. The input passes through a pooling layer with a 2 x 2 kernel size after each convolutional layer, which reduces the features map's dimensions by summarizing the features presented in a region and preventing over-fitting by down sampling; additionally, we used a dropout layer after each pooling layer to keep neurons in a layer from synchronously optimizing their weights and converging to the same goal; our model's dropout rate is 0.3, meaning that 30% of the layer's neurons will be randomly dropped in each epoch. When moving from the pooled features map to the fully connected layer, all of the resulting 2D arrays go via the flatten layer and are transformed into single-dimensional long continuous linear vectors, as shown in Fig. 4.4. Each and every output pixel from the convolutional layers is linked to three output classes in the fully connected layer. Ultimately, we converted the three completely linked layer units 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.

Result-We provide graphical representations in Figures 4.5, 4.6 and 4.7 for a thorough analysis of the performance measures of our suggested model, including accuracy, loss, precision, recall, and AUC. These graphs offer a nuanced picture of the model's performance dynamics by illuminating the behavior of the model across a range of measures during the training and validation stages.

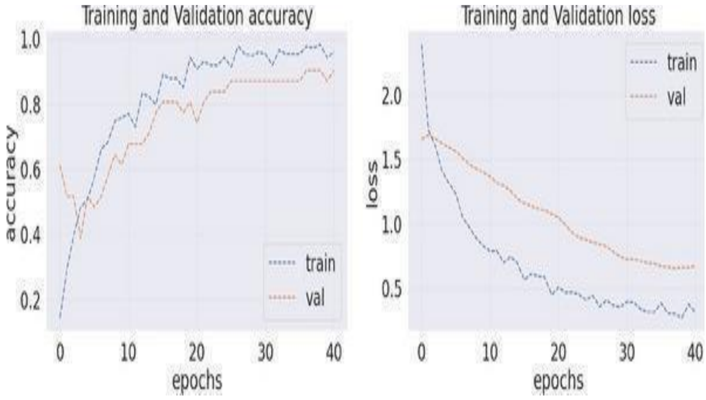

Fig 4.5. Accuracy Graph during Training and Validation

On the left, we can see the accuracy during training and validation. On the right, we can see the loss during training and validation.

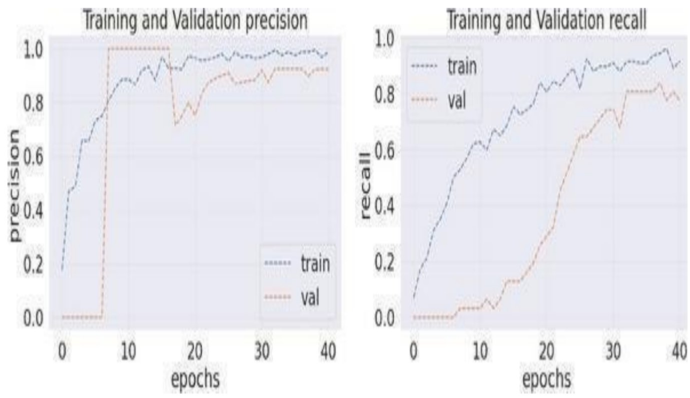

Fig 4.6. Accuracy Graph during Training and Validation Precision and Recall.

On the left and right sides of the picture are graphs of training and validation precision and recall.

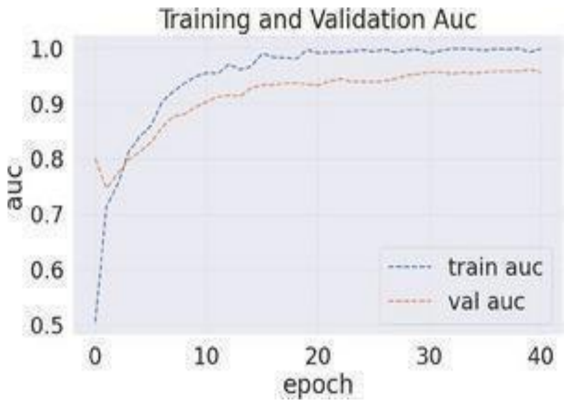

Fig 4.7. Accuracy Graph during Training & Validation Auc

AUC curve for proposed model which stands for "area under the curve".

When our suggested hair scalp disease classification model is examined, Fig 4.8 for the test set shows that it performs admirably in a variety of disease categories. Notably, the model attains exceptional precision scores, achieving perfect precision (1.00) for Effluvium, Dissecting

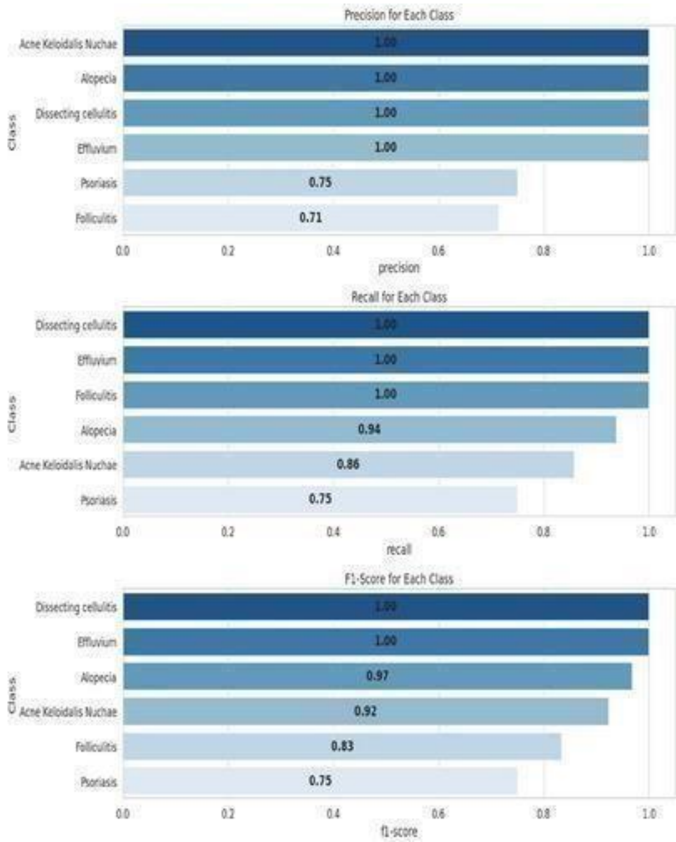

Fig 4.8. Precision, Recall and F1-score

Model performs on hair scalp disease classification, showing precision, recall and F1-score metrics for six diseases, highlighting strengths, and area for improvement.

5. Conclusion

In conclusion, the project represents a major advancement in the fields of dermatology and medical technology by utilizing machine learning and image processing to diagnose diseases of the hair and scalp. By integrating cutting-edge machine learning algorithms and image processing techniques, this study has demonstrated the ability to significantly change the early detection and diagnosis of hair and scalp issues.

Several significant results and outcomes of the project include the following:

Accuracy and Precision: The proven model has frequently done better in identifying a range of hair and scalp ailments than traditional diagnostic methods.

Early Detection: Should the research be effective in recognizing illnesses prior to symptoms manifesting, this may lead to timely treatments that enhance patient outcomes and reduce the severity of problems.

Accessibility: By using technology, this project can give a broader population— including underprivileged groups and rural areas—access to the diagnosis of hair and scalp illnesses. Data Collection: The project has contributed useful image data of the hair and scalp, which will advance this area of research.

Automation: Faster diagnosis and fewer work for medical professionals are two benefits of automating disease detection, which could relieve the burden on healthcare systems.

Future Directions: The project creates avenues for further research and development, including the integration of telemedicine applications, real-time monitoring, and algorithm enhancement for even greater accuracy.

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