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Harnessing Deep Learning for Scalp and Hair Disease Classification: A Comparative Study of Convolutional Neural Networks Architectures

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ABSTRACT

Scalp and hair diseases, affecting millions worldwide, pose significant challenges regarding accurate diagnosis and effective treatment. Traditionally reliant on expert evaluation, these conditions can often be misdiagnosed due to their complex and overlapping symptoms. In recent times, especially in information technology, convolutional neural networks (CNNS) have become more prominent thanks to their ability to analyse and process image data for classification and recognition tasks. CNNs learn to recognize patterns from images through convolutional layers to detect characteristic features in image sand have revolutionized the field of image recognition, offering promising applications in medical diagnostics. Despite their potential, few studies have thoroughly explored the capabilities of multiple CNN architecturesin the context of dermatology. This study aims to bridge this gap by evaluating the effectiveness of several CNN models—VGG16, VGG$_{19}$, Inception-V3, ResNet50, and ResNet152—in detecting scalp and hair diseases. The findings indicate that VGG16 and VGG$_{19}$ consistently outper for mother models in accuracy across all disease categories, demon strating their robustness and reliability for this application. By providing a comparative analysis of these architectures with a user interface (UI), we seek to advance automated diagnostic methods, ultimately enhancing clinical decision-making and patient care.

Subject Categories and Descriptors: [I.5 Pattern Recognition Models]; [I.4 Image Processing and Computer Vision]; [I.4.10 Image Representation] ; [J.3 Medical information systems]

General Terms: Deep Learning, Hair Disease Classification, Convolutional Neural Networks

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1. Introduction

Hair serves multiple functions in human biology and society, fulfilling physiological and behavioral roles. Hair serves as a physiological means of safeguarding the scalp from *UV* radiation, thermal harm, and physical harm, hence preserving the overall health of the scalp, as shown in Takagi et al study [1]. Moreover, hair is crucial in defining one's identity and cultural representation, substantially influencing self-confidence and interpersonal relationships [2]. Although hair is resilient, it can still be affected by many disorders that can weaken its structure and overall health.

Most hair and scalp diseases are not detected in the early stage. There are occasions when the patient does not identify the hair loss from the regular fall of hair. Most of the time, it takes a lot of time to diagnose hair diseases since it has to be done by qualified dermatologists, who later perform visual and other medical tests. Scalp and hair illnesses comprise various conditions that can substantially impact a person's physical appearance and mental well-being. Typical disorders include Alopecia Areata [3, 4], Psoriasis [5], Seborrheic Dermatitis [6], and Fungal Infections [7], each posing distinct difficulties in diagnosis and treatment. These diseases are both prevalent and exhibit a range of severity and symptoms, impacting millions of humans worldwide. Specifically, alopecia-areata alone impacts around 2% of the population at some stage of their life span [8]. These disorders have effects that go beyond only medical symptoms, frequently causing significant psychological suffering, lowered self-esteem, and social anxiety.

Diagnosing scalp and hair illnesses is challenging for dermatologists due to over lapping symptoms and subjective visual inspections, often leading to inconsistencies and misdiagnoses. Additionally, the growing demand for dermatological care strains healthcare systems, causing delays in diagnosis and treatment. To address this, our study compares *CNN* architectures (*VGG*-16, *VGG*-19, Inception-v3, ResNet50, ResNet152) for classifying scalp and hair disorders usinga unique dataset from Kaggle with ten illness categories. The study also includes a web-based platform to help healthcare professionals detect these diseases more accurately and efficiently.

2. Related Works

Multiple research studies have been conducted to categorize and identify various hair disorders. Nevertheless, most research endeavors are bound by constraints and limitations, preventing them from providing a comprehensive solution. This section aims to enhance comprehension of the limitations of prior research by examining the merits and drawbacks of publications and proposing strategies to address such disadvantages. The etiopathogenesis requires a variety of genetic, endocrine, immune, or inflammatory factors, each of which necessitates its treatment for successful management. [9]

The first case study to apply modern machine learning to the diagnosis and analysis of hairy scalp issues was instituted by Wang et al. [10]. Several studies have employed deep learning techniques to categorize diseases, such as a 2023 study by Rao et al. [11] on the automated prediction of skin diseases. The study proposed using deep convolutional neural networks (*DCNN*) to classify skin diseases and enhance their performance by employing the binary butterfly optimization approach (*BBOA*). The Kaggle HAM10000dataset comprises 10,000 images. The model, which underwent 20epochs, was trained in a mere 99.67 seconds and achieved an accuracy of 91.02%.

In 2022, Ahammed et al. introduced a method based on machine learning to detect and classify skin diseases. Their approach involved using image segmentation techniques [12]. The paper detailed the application of morphological filtering for digital hair removal and Gaussian filtering for image denoising. The Harnessing Deep Learning for Scalp and Hair Disease Classification Grey Level Co-occurrence Matrix (*GLCM*) and statistical features are utilized to process skin images. Decision Tree (DT), Support Vector Machine (*SVM*), and K-Nearest Neighbour (*KNN*) algorithms are used to extract features and classify various types of skin diseases, including melanoma, melanocytic, basal cell carcinoma, nevus, benign and actinic keratoses, vascular lesions, dermatofibroma, and squamous cell carcinoma. Performing model validation using the ISIC 2019 challenge and HAM10000 datasets [13]. According to the study, SVM demonstrates superior performance compared to other methods, achieving an average accuracy of 95-97%. Kim et al evaluated the performance of ResNet, ResNeXt, DenseNet, and XceptionNet, but with a limited dataset. [14].

The recent study achieved higher training and validation accuracy using the 2*D* convolutional neural network (*CNN*) model. [15]. The 2*D CNN* model was used in another work, which resulted in higher training and validation accuracy. [16] Many studies have recently deployed deep learning techniques, and they significantly contribute to leveraging technology for improved skin care management. [17], [18], [19].

Rafay et al. [20] proposed using an Efficient Net model to classify 31 skin diseases. Their work involved a manually curated dataset combining two separate sources, encompassing 31 skin conditions. They used a pre-trained model with tested architectures such as Efficient Net, ResNet, and *VGG*. We understand that other deep learning methods have been successfully used for skin disease classification, including *DCNN+BBOA*, *SVM*, *MC-SVM*, *KNN*, *DT+RF*, and ResNet50. A common challenge is that predictive accuracy drops when scaling to large datasets. The past research has primarily focused on skin diseases, with no studies addressing hair diseases specifically. Using sophisticated instruments and techniques ensures advances in skin care treatment. The mobile scalp hair imaging microscope, an app for mobile devices, an artificial intelligence (AI) training server located in the cloud, and an online management platform have proven to yield better systems. [21].

3. Methodology

This section will elucidate the pipeline of our methodologies and elaborate on each part in more detail to approach the best solution for hair disease diagnosis. In Figure 1, this part will present the data collection and training process and the designed platforms for testing the trained model. Finally, the features involved are explained in detail.

Figure 1 presents a step-by-step approach for creating a classification system that utilizes *CNN* models to analyze picture data, specifically to identify scalp and hair illnesses. The following is a comprehensive elucidation of each stage in the procedure:

3.1 Collect Dataset

This initial step involves gathering a comprehensive dataset of images relevant to the study. In the context of hair and scalp disease classification, this could include clinical images of various conditions affecting the scalp and hair.

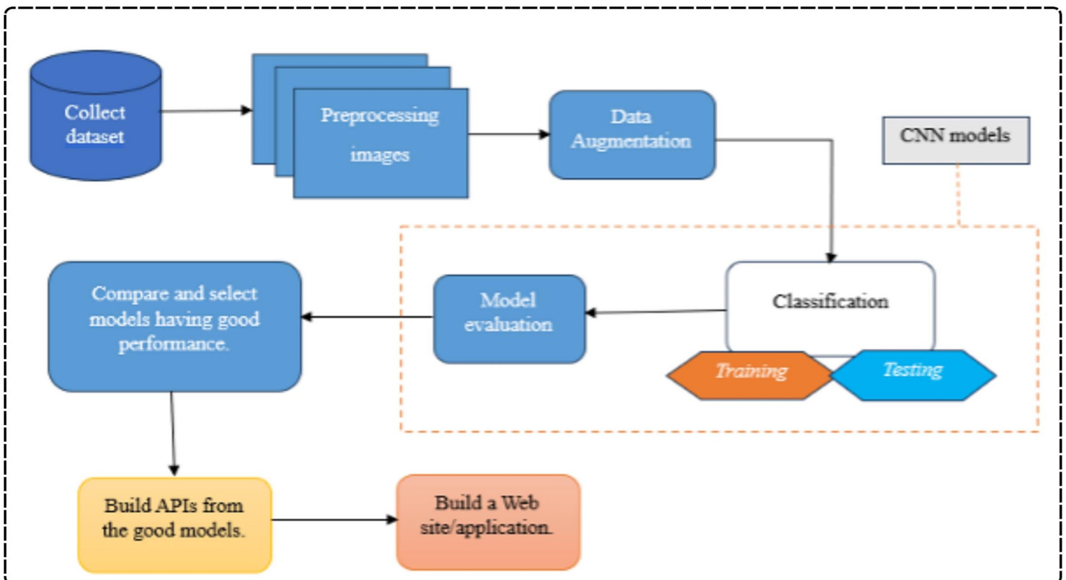

Figure 1. Overview of the methodological approach in our study

3.2 Data Preprocessing and Augmentation

This is a technique of generating variations from the original data to generate more data for training. This stage may clean and prepare images for analysis. Resizing images, normalizing pixel values, and removing noise or irrelevant background information are preprocessing steps. Augmentation techniques also create variations of images to expand the dataset artificially. Flipping, rotating, cropping, and adjusting brightness and contrast are examples.

3.3 CNN Models

Multiple CNN architectures (VGG16, VGG_{19}, Inception-V3, ResNet50, ResNet152) are utilized for the classification task. These models have different strengths and complexities, providing various perspectives on feature extraction and classification.

3.4 Classification

• **Training:** The training process involves using the augmented and preprocessed images to train the CNN models. This step adjusts the models' weights to minimize errors in predicting the correct classification labels.

• **Testing:** After training, the models are tested on a separate set of images to evaluate their performance and generalization capabilities.

3.5 Model Evaluation

The models' performance is evaluated using various metrics such as accuracy, precision, recall, and F1-score. This evaluation helps in understanding the strengths and weaknesses of each model.

3.6 Dataset Acquisition

While the main dataset, collected from Kaggle, consists of 12,000 images, its diversity is quite minimal; for details, it only includes 10 common scalp and hair diseases, leaving out many rarer conditions. Adding more images from different sources and covering rarer diseases could help the model learn a wider range of features, leading to better generalization and reducing the risk of overfitting. This is especially important for real clinical diagnosis, where disease cases can be more complex than what's in this dataset .

Figure 2. Sample of hair disease images collected from Kaggle[13]

Sets	Quantity	Percentage
Training	10,024	80%
Validation	1,253	10%
Testing	1,253	10%

Table 1. The data distribution in the training, validation, and testing sets is represented in terms of quantity and percentage

This platform provides this research with high-resolution photographs of individuals exhibiting a range of scalp and hair disorders. The photos were enhanced with publicly accessible databases focusing on dermatological disorders, guaranteeing a diverse representation of various disease kinds and phases. The quality control techniques involved meticulously examining photographs by seasoned dermatologists to verify the precision of diagnoses and guarantee the elimination of any images with in adequate illumination or focus problems. Themeticulous method of obtaining the information created a strong groundwork for developing and validating the CNN models utilized in the study.

The dataset comprises two parts a Kaggle dataset provided by Sundar Annamala et al. [22] that contains 12,000 images of hair diseases and 530 images collected from the Internet, as shown in Figure 2. Each of these is labeled intoten classes of hair diseases, including Alopecia Areata, Contact Dermatitis, Folliculitis, Head Lice, Lichen Planus, Male Pattern Baldness, Psoriasis, Seborrheic Dermatitis, Telogen Effluvium, Tinea Capitis. This dataset is divided into threesub-datasets: training, Validating, and Testing, which are described in Table 1.

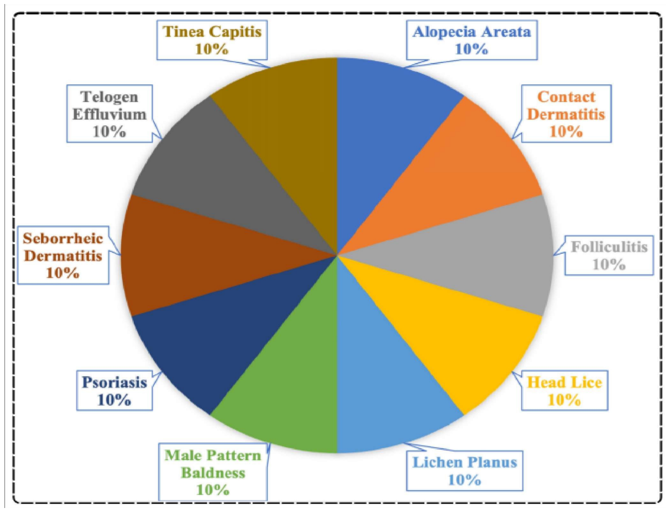

Figure 3. The distribution of ten types of scalp and hair diseases in the collected dataset

The pie chart in Figure 3 depicts the allocation of different scalp and hair illnesses, with each ailment accounting for an equal share of 10%. This indicates that these diseases have the same frequency rate within the dataset or study environment. This ensures a fair and unbiased representation for analytical and diagnostic purposes, particularly when training artificial intelligence. Besides, scalp and hair illnesses refer to various conditions that impact the hair and scalp, resulting in discomfort, aesthetic worries, and, occasionally, substantial health problems. Those diseases are classified into several groups, such as easy, medium, and hard to detect, depending on their features and the doctor's experience:

- **Easy:** Head Lice, Seborrheic Dermatitis, Male Pattern Baldness

- **Medium:** Psoriasis, Contact Dermatitis, Telogen Effluvium

- **Hard:** Alopecia Areata, Tinea Capitis, Folliculitis

Choosing and training a suitable convolutional neural network (*CNN*) model is essential for precise diagnosis and classification due to the varied characteristics of each scalp and hair illness. By testing and evaluating each model against these disease categories, researchers can determine the most effective C*NN* architecture for each condition, ultimately improving diagnostic accuracy and patient care. care outcomes

3.7 Comparative Analysis of CNN Variants

In this section, our study evaluated the performance of five prominent architectures:VGG16, VGG19, Inception-V3, ResNet-50, and ResNet-152. Each model offers distinct advantages in terms of architectural design and feature extraction capabilities. Those models were compared using accuracy, precision, recall, and F1-score metrics to validate and test which achieved the highest accuracy. This analysis highlights the trade-offs between model complexity and performance, underscoring the importance of selecting an architecture that aligns with the specific requirements of real-world applications, such as deployment on resource-constrained devices or in clinical settings where rapid results are essential.

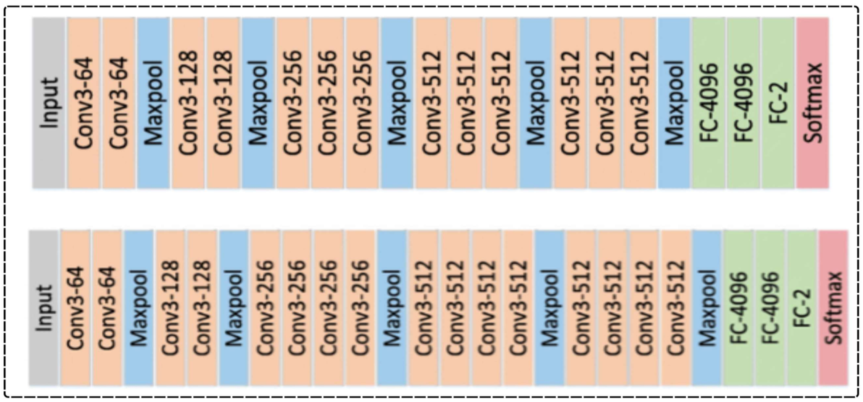

Figure 4. The general overview of *VGG*-16 (Above) and *VGG*-$_{19}$ (Below) architecture

VGG-16 and *VGG*-$_{19}$ *VGG*16 and *VGG*$_{19}$ are convolutional neural networks renowned for their simplicity and efficacy in image classification tasks, specifically in identifying scalp and hair diseases. These models are composed of sequential 3x3 convolutional layers, allowing them to capture intricate patterns in images effectively. Using a small convolutional layer, the VGG models can detect small features in images, such as small details of the scalp and hair, or pathological symptoms such as swelling and skin damage. Furthermore, the main difference between the VGG models here can be mentioned as the number of weight layers. With VGG16, the model has 13 convolutional layers and three fully connected layers. The convolutional layers are usually arranged consecutively and followed by max-pooling layers. It can reduce the size of the spatial features while preserving important information, as well as significantly reduce the possibility of overfitting the model. A version with better performance is VGG$_{19}$, with 19 layers, which could improve performance in image recognition tasks. Furthermore, the VGG models were pre-trained for image recognition tasks with the Image Net dataset (over 14 million images), so by using transfer learning, which means based on the knowledge of the available data, the model trained for scalp and hair disease diagnosis will be able to detect basic pixels, corners, edges, etc. easily.

Inception-*v*3 is an efficient *CNN* architecture that excels at handling complex image classification tasks, such as identifying scalp and hair diseases. Its inception modules combine filters of different sizes (1x1, 3x3, 5x5)within the same layer, allowing it to capture fine and large-scale features. This is especially useful for medical images, where details at various scales matter. Using factorized convolutions reduces computational load while maintaining the ability to extract complex patterns. Auxiliary classifiers help improve gradient flow, preventing the vanishing gradient problem, which is crucial for smaller medical datasets. Inception-V3's structure, with its pooling layers, ensures a balance between efficiency and accuracy, making it a suitable choice for medical image analysis.

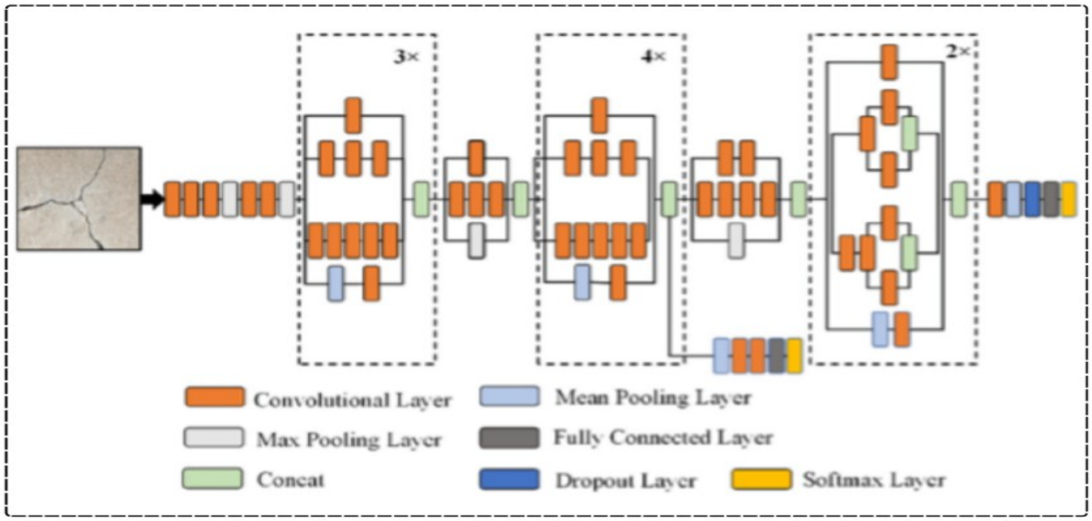

Figure 5. The general overview of Inception-*V*3 architecture [14]

Resnet-50 and Resnet-152 are included in the Residual Networks family, utilising residual blocks that allow the training of deep networks by solving the vanishing gradient. However, they would not be quite suitable for the classification of diseases of the scalp and hair. In the tremendous depth, such as 50-layer depth inResNet50 and 152 layers in ResNet152, there will be a multiple risk of overfitting, especially if working with small medical datasets that do not contain diverse data. The complexity of these models requires significant computational resources, which may be excessive for the relatively more straightforward patterns in images of scalp and hair diseases. As a result, while residual connections in models like ResNet are beneficial for maintaining gradient flow, they may not provide a significant advantage for this classification task. In this case, increasing the network depth does not necessarily lead to better performance. Therefore, ResNet models might be overkill, especially in environments with limited data, where their high computational cost could outweigh the benefits of this particular application.

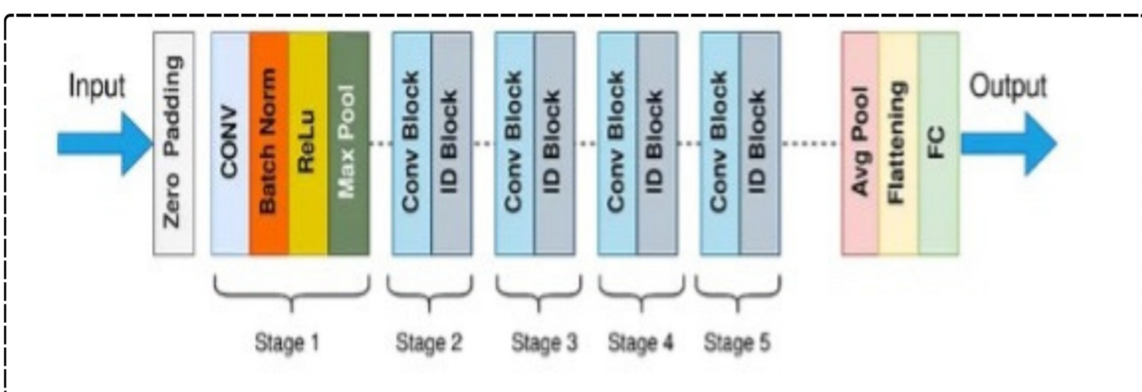

Figure 6. The general overview of ResNet-50 architecture

In conclusion, head lice and seborrheic dermatitis are easier to detect, while alopecia areata and folliculitis are harder due to overlapping traits. VGG16 and VGG19 excel in recognizing complex features. Careful data augmentation is key to maintaining accuracy, especially for location-specific diseases like alopecia areata.

4. Experimental Results and Implementation

4.1 Evaluation Metrics

The trained models are compared based on the following evaluation metrics: Test Accuracy (%), Loss (%), Precision, Recall, and F1-score.The accuracy, representing the proportion of correctly classified images, offersa baseline assessment of model performance. However, accuracy alone can be misleading, especially in cases of class imbalance. To address this, precision and recall are considered; precision measures the accuracy of optimistic predictions, indicating how often predicted positive cases are actual positives, while recall assesses the model's ability to capture all actual positive instances. Moreover, the F1-score, the harmonic mean of accuracy and recall, offers a balanced assessment of these two measures, especially when imbalanced class distributions.

Table 2 comprehensively compares *CNN* architectures, including *VGG*-16, *VGG*-19, Inception-*V*3, ResNet-50, and ResNet-152.The evaluation is based on performance metrics such as test accuracy, loss, precision, recall, and F1-score. Each model exhibits distinct advantages and disadvantages, which can provide valuable information regarding their suitability for precise and dependable disease classification.

The *VGG*-16 and *VGG*-19 models demonstrate exceptional performance, attaining test accuracies of 96.81% and 96.73%, respectively, and low loss values of 20.13% and 19.94%,respectively. These models also exhibit a high precision, recall, and F1-scores of 0.97, demonstrating their consistent accuracy in predicting positive situations and collecting all relevant examples.

The Inception-*V*3 model demonstrates a test accuracy of 95.13% and a loss of 100.74%, indicating a tiny decrease in accuracy. However, it still shows impressive precision, recall, and an F1-score of 0.95, indicating its strong ability to diagnose hair illnesses. On the other hand, the ResNet-50 and ResNet-152 models

Classification		**Evaluation Metrics**			
Models	**Test Accuracy (%)**	**Loss (%)**	**Precision**	**Recall**	**F1-Score**
VGG-16	96.81	20.13	0.97	0.97	0.97
VGG-19	96.73	19.94	0.97	0.97	0.97
Inception-V3	95.13	100.74	0.95	0.95	0.95
ResNet-50	49.16	151.75	0.71	0.49	0.45
ResNet152	36.87	181.54	0.72	0.37	0.37

Table 2. Comparison between a variety of CNN models with evaluation metrics

demonstrate notably lower test accuracies of 49.16% and 36.87% and larger loss values of 151.75% and 181.54%, respectively. Additionally, these models exhibit reduced precision, recall, and F1-scores, which suggests difficulties in detecting disease cases and managing imbalances in class distribution.

The comparative examination of *CNN* models demonstrates that *VGG*-16and *VGG*-$_{19}$ outperform other models in accurately classifying scalp and hair illnesses. This higher performance is related to their high accuracy and robust precision-recall balance. Despite Inception-V3 having somewhat lower accuracy, its consistent performance across evaluation measures makes it a feasible choice for this classification assignment. On the other hand, the less-than-ideal outcomes are those of ResNet-50 and ResNet-152. Although ResNet generally performs well in image classification tasks, in this study, ResNet's performance struggled, especially at high loss values. This can be explained by the complexity of the ResNet architecture with many layers (50 and 152 layers),which requires extensive and diverse datasets to optimize the weights effectively. This is because the dataset in the study may not be large enough to support the training of deep ResNet models, leading to over fitting. In addition, the complex structure of ResNet may have difficulty learning features from images, especially when the dataset is small and not diverse. This explains why ResNet cannot distinguish hair and scalp diseases well in the study. Moreover, the performance of deep learning models depends not only on their architecture but also on their hyperparameters. For example, too high a learning rate can cause the model to miss the optimal score during training, or too small a batch size can reduce the model's generalization ability. Therefore, careful tuning of hyperparameters is significant to optimize model performance. These findings emphasise the significance of choosing a suitable *CNN* structure according to the specific requirements of the classification task to improve diagnostic accuracy and reliability.

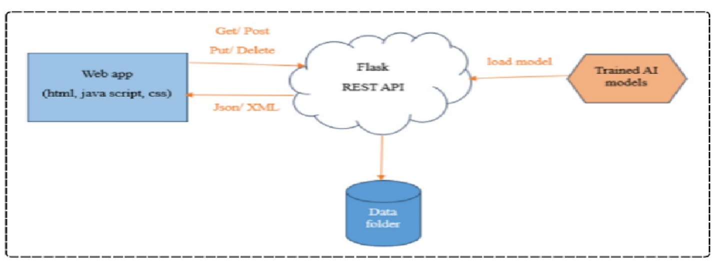

Figure 7. The workflow of our web application for end-users to test with the trained model

5. Discussion, Conclusion and Future Works

The assessment of various *CNN* models for identifying scalp and hair illnesses revealed key insights into their effectiveness. Inception*V3* consistently out perform do their models' accuracy across all disease categories, demonstratingits reliability, especially in complex cases like psoriasis. Its strong performance highlights its potential for clinical use. However, the differences in performance between *VGG*-16 and *VGG*-$_{19}$, particularly for psoriasis diagnosis, emphasize the importance of selecting the appropriate model based on the dataset and disease characteristics.

In summary, this study underscores the significant potential of *CNN* models in dermatological diagnostics by enabling automated illness identification. *VGG* - 16 and *VGG* -19 stood out as reliable models for accurately classifying scalp and hair disorders, improving diagnostic processes and patient outcomes. The findings contribute to growing evidence supporting AI in healthcare while guiding the selection of appropriate AI tools. Despite positive results, the study acknowledges limitations like limited sample diversity and calls for further testing on broader datasets for wider applicability.

Deep learning, coupled with cloud computing techniques and embedded systems, is also found to offer more reliable results. (24) *CNN* models with better accuracy and interpretability indicate a significant advancement in scalp detection, which ensures the promise of more reliable and accessible identification techniques. (25) Deep learning still needs to be enhanced in precision and reliability. (26)

Future research should address the limitations identified in this study to improve the effectiveness of *CNN* models in medical diagnostics. Expanding the dataset with broader images and conditions will enhance model applicability and reliability. Applying ensemble models and incorporating attention mechanisms can improve accuracy and diagnostic precision. Exploring AI's ethical and regulatory implications in healthcare is essential, emphasizing interdisciplinary collaboration to ensure accurate and reliable AI-based medical diagnoses, with experts playing a key role invalidation and verification.

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