Scalp Disorder Imaging: How Deep Learning and Explainable Artificial Intelligence are Revolutionizing Diagnosis and Treatment

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***Abstract*—Scalp disorders, affecting millions worldwide, significantly impact both physical and mental health. Deep learning has emerged as a promising tool for automated diagnosis, but ensuring model transparency and reliability is crucial. This review explores the integration of explainable AI (XAI) techniques to enhance the interpretability of deep learning models in scalp disorder diagnosis. We analyzed recent studies employing deep learning models to classify scalp disorders from image data and used XAI methods to understand the models' decision-making processes and identify potential biases. While deep learning has shown promising results, challenges such as data quality and model interpretability persist. Future research should focus on expanding the capabilities of deep learning models for real-time detection and severity prediction, while addressing limitations in data diversity and ensuring the generalizability of models across different populations. The integration of XAI techniques is essential for fostering trust in AI-powered scalp disease diagnosis and facilitating their widespread adoption in clinical practice.**

Keywords*—*Scalp disorders; artificial intelligence; explainable artificial intelligence; deep learning; interpretability

I. Introduction

In recent times, the integration of AI in healthcare has transitioned from theoretical research to practical implementations in clinical settings. This includes areas such as telemedicine, the utilization of robots in surgical settings, and the management of electronic health records. Medical imaging stands out as one of the most recognized applications, constituting 90% of all healthcare data [1]. AI demonstrates promising capabilities in diagnosing and classifying various diseases, particularly in dermatological conditions, where it assists in the identification and categorization of skin issues, including conditions related to the scalp and hair.

Despite these advances, a significant gap in research remains regarding the deployment of deep learning (DL) models in medical imaging, particularly in clinical settings. While current DL models, inspired by neural networks in the human brain, include notable architectures such as Faster R-CNN [2], VGG-net [3], and those based on ImageNet [4] offer impressive accuracy in tasks such as image recognition and classification. their lack of interpretability presents a major challenge, especially in complex areas like dermatology and scalp and hair disorder diagnostics [5]. This issue has spurred growing interest in the role of eXplainable AI (XAI), which aims to make the decision processes of DL models transparent. XAI is not only beneficial for machine learning (ML) researchers but is also vital for clinicians and patients who rely on these models to make informed healthcare decisions. By making AI more interpretable, XAI fosters trust in clinical applications, addressing a crucial need for greater transparency in AI-driven diagnostics.

This review aims to comprehensively examine the progress and challenges in utilizing XAI and DL methodologies for analyzing medical imaging data, specifically for scalp and hair disorder diagnostics. Through an extensive review of existing studies, this paper will highlight the contributions and limitations of various DL models applied to dermatological imaging and evaluate the effectiveness of XAI techniques in enhancing their interpretability and clinical relevance. This examination includes an analysis of how XAI techniques can improve transparency in AI-based diagnostics, particularly for non-expert stakeholders, such as clinicians and patients, who require comprehensible insights into AI-driven assessments.

The significance of this review lies in addressing the critical need for interpretable AI systems in dermatology, with a focus on the largely unexplored domain of scalp and hair disorder imaging. By synthesizing existing findings, this paper aims to provide a reference for developing clinically applicable AI frameworks that enhance both accuracy and interpretability. Ultimately, this review not only consolidates current knowledge but also serves as a foundation for future research aimed at creating trustworthy and effective AI-driven diagnostic tools across dermatological and broader medical applications.

The structure of this paper is organized as follows: Section II details the materials and methods applied in various studies, specifically focusing on the deep learning and XAI techniques employed in scalp and hair disorder diagnostics. Section III presents the results gathered from these studies, offering insights into the effectiveness of each approach. Section IV provides a discussion that highlights both the strengths and limitations of the reviewed studies, analyzing their contributions and identifying potential gaps. Finally, Section V concludes the paper, summarizing key findings and suggesting directions for future research.

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II. Materials and Method

A. Artificial Intelligence in Scalp Disorder Diagnosis

Scalp disorders are recognized as dermatological or medical issues associated with the well-being of the scalp and hair, attributed to the abundance of hair follicles and elevated sebum production. These disorders may include dandruff, seborrheic, folliculitis, tinea capitis, psoriasis, are widespread conditions affecting adults globally. Scalp psoriasis, impacting approximately 2% of the Western population [6], and dandruff, with a global prevalence of around 50% [7], contribute significantly to these concerns. These conditions not only affect physical health but also exert a substantial influence on mental well-being, contributing to stress, anxiety, or depression [8], [9]. This impact is particularly noticeable in societies where significant of appearance holds considerable weight, as observed in places like South Korea, where lookism can have implications for health [10].

Therefore, the diagnosis and classification are crucial, as scalp disorders frequently exhibit similar clinical manifestations [11]. The way to diagnosis scalp related-problems could be use various data type, including: medical imaging, clinical notes, and scalp biopsy laboratory test result; however, scalps biopsies can cause risk such as bleeding, pain, and infection meanwhile clinical notes may be subjective and vary in quality, potentially leading to biases or inaccuracies in the diagnostic process among these approaches, scalp imaging stands out as it offers a non-invasive and direct visualization of the scalp. Advanced imaging technologies like dermoscopy (trichoscopy) and optical coherence tomography (OCT), enhance the diagnostic capabilities by providing magnified insights into structural and morphological changes at a microscopic level [12]. For dermatologists, this means enhanced diagnostic capabilities without the associated risks of scalp biopsies. On the patient's side, the non-invasiveness and direct visual feedback contribute to a more comfortable and accessible diagnostic experience. However, a concerning trend is observed, where people frequently seek diagnoses from non-professionals in hair salons rather than consulting dermatologists. This trend has contributed to a worsening state in the overall condition of scalp problems.

In order to overcome these challenges, the advances of AI applications in dermatology have introduced a transformative model shift, revolutionizing how we approach the diagnosis and treatment of scalp hair-related problems. AI, including ML and DL, has become widespread components in any medical analysis workflows and facilitating the path for the real-world diagnostic integration of solutions based on AI [13]. In the context of scalp health, the application of AI holds the promise of not only enhancing precision in identifying and classifying various scalp conditions but also revolutionizing the therapeutic strategies employed, such as providing an opportunity for patients to engage in self-diagnosis [14]. This intersection of AI and dermatology prompts a renewed research interest, particularly in the early detection and diagnosis of scalp hair diseases.

However, complex ML algorithms pose challenges in comprehending their decision-making processes, specifically in complicated tasks such as scalp hair imaging classification. In order to effectively tackle this issue, the implementation of XAI presents a distinctive opportunity, benefiting not only AI experts but also non-experts like medical doctors and patients [15].

B. Advanced Machine Learning in Scalp Imaging

Scalp imaging can be categorized into various modalities, each offering unique insights into different aspects of scalp health. Dermoscopy, or surface microscopy [16], utilizes a handheld device with magnification and lighting to visualize pigmented cutaneous lesions and assess hair follicles, patterns of hair loss, and various scalp conditions. OCT captures high-resolution, cross-sectional images of biological tissues, revealing structural changes in the skin and hair follicles. In Vivo Reflectance Confocal Microscopy (RCM) provides live visualization [17] of cellular structures in the scalp at a high resolution, generated high-quality images of the hair shaft junctions at 1µm spacing, facilitating a comprehensive analysis of the hair structure. In the field of ML and DL, several studies have predominantly utilized portable magnification imaging microscopes [2], [18], [19], [20] or dermoscopy data [21], [22], [23], in comparison to OCT studies [24] and RCM, due to higher costs and challenges in obtaining data. Additionally, limited training programs for RCM [25] contribute to subjective variability in diagnoses.

C. Limitations of Machine Learning in Scalp Disorder Imaging

Since 2014, studies employing ML for scalp imaging classification have evolved, transitioning from unsupervised learning approaches [26], [27] to more complex deep-learning based method [3], [18], [28]. These studies have utilized datasets ranging from small to mid-size, achieving accuracies typically in the mid-80s to low 90s. However, the domain of scalp disorder imaging still faces persistent challenges. Notably in contrast to research studies focused on other skin areas. In these areas, datasets commonly surpass 100,000 images [29], [30]. Moreover, the datasets within scalp disorder imaging exhibit imbalances, further compounded by a deficiency in interpretability and explainability.

As a result, these challenges make it difficult to smoothly apply these technologies in a clinical setting. To address these issues, there is a pressing need to explore new research avenues, particularly in comparison to the advancements made in skin disease classification within the dermatology realm.

D. Advancements in Integrating Deep Learning Models and Explainable AI for Scalp Disorder Imaging

Numerous researchers have dedicated their efforts to advance the deployment of ML models for the classification of scalp hair disorders. The evolution of ML into DL models, including the integration of XAI has been revolutionary. This commitment involves implementing XAI to make it possible to identify and address any potential biases in the model's decision-making process, aiming to increase trust for clinical applications. The following showcases how these advancements can be presented:

1) Convolutional neural network variations model: With the increasing use of DL models in imaging classification tasks, the foundational technique of Convolutional Neural Networks (CNNs) plays a pivotal role in developing recent models. CNNs consist of various layers, such as convolutional, activation, and pooling layers. The inclusion of one or more Fully-Connected layers (FC) in the network is essential for generating final output predictions. Additionally, dropout layers have been incorporated into the architecture to address the overfitting issue and enhance the model's robustness. The strategic use of dropout layers aids in preventing the network from relying too heavily on specific connections during training, promoting a more generalized and resilient model.

To demonstrate how different models respond to scalp imaging disorder classification tasks, well-known models have been applied. These models can be categorized into two main architectures: one-stage architecture and two-stage architecture. In the two-stage approach, exemplified by Faster R-CNN (Region-based Convolutional Neural Network) [31], the Region Proposal Network (RPN) represents a significant advancement. By sharing convolutional layers with the object detection network, the RPN efficiently generates region proposals directly from the convolutional feature maps, avoiding the need for external proposal generation methods. The RPN evaluates a set of anchor boxes at different scales and aspect ratios, predicting their likelihood of containing an object and refining their coordinates.

On the other hand, one-stage CNNs follow a more streamlined approach, performing simultaneous object detection and localization without a separate region proposal stage. These models directly predict object localization and classification within an image, making them efficient for real-time object detection. However, it's essential to note that they may not always achieve the same level of accuracy as two-stage models in certain situations. One example of one-stage CNNs is the Single Shot MultiBox Detector (SSD) [32].

2) Vision transformers (ViTs): Traditional CNN architectures rely on convolutional layers to extract features from images. These layers progressively learn to identify low-level features like edges and textures, ultimately building towards higher-level features for classification. However, a recent advancement in image classification is the emergence of Vision Transformers (ViTs) [33]. Unlike CNNs, ViTs forego convolutional layers entirely. Instead, they split the image into patches, process them using self-attention mechanisms, and progressively learn relationships between different image regions. This approach allows ViTs to potentially capture long-range dependencies within images that might be missed by CNNs with localized filters. Fig. 1 represents the concept of ViT proposed in Dosovitskiy et al.'s study [33].

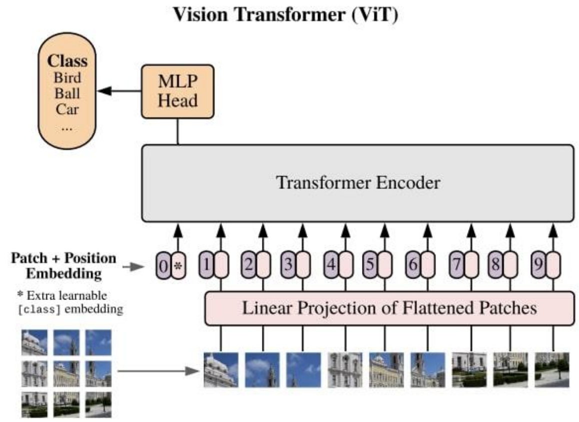

Fig. 1. The concept of vision transformers.

3) Gradient-weighted class activation mapping (Grad-CAM): Ramprasaath and his team [34] introduced a technique aimed at providing visual representations of the decision-making process of deep neural networks, particularly convolutional network. At a high level, the approach involves processing an image as input data and creating a model that is truncated at a specific layer to generate visual representations of the areas in input images that have the most impact on the network's predictions.

Operationally, the method conducts a forward pass of the input image through the network, and the subsequent prediction triggers a backward pass to the sensitivity of the predicted class score to changes in the feature maps. Global Average Pooling (GAP) is then applied to globally average these gradients across each feature map, generating a class-discriminative localization map. This map is utilized as weights to compute a weighted sum of the feature maps, emphasizing regions crucial for the prediction. Following a Rectified Linear Unit (ReLU) activation and up-sampling to match the input image's dimensions, the final heatmap is produced, producing visual maps to show important zones influencing the network's decision.

Nevertheless, Grad-CAM faces limitations in highlighting fine-grained features due to its inability for pixel-level gradient visualization. The down-sampling during convolution and the subsequent need for up-sampling via bilinear interpolation result in a loss of resolution, impacting the accuracy of explanation results. Additionally, inconsistencies between Grad-CAM and the actual model behavior diminish the reliability of its interpretations. These challenges underscore the necessity for improvements in Grad-CAM to enhance precision and alignment with the intricacies of the original model. Fig. 2 represents the concept of Grad-CAM proposed in Ramprasaath et al.'s study [35].

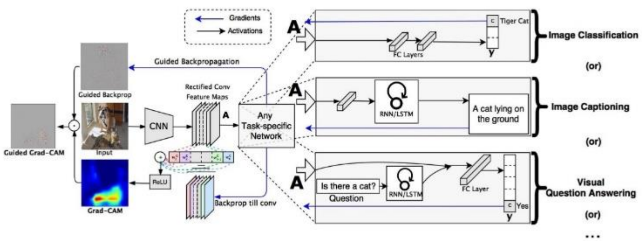

Fig. 2. The overview concept of Grad-CAM by Ramprasaath et al. [34].

4) Locally interpretable model-agnostic explanation (LIME): Local Interpretable Model-agnostic Explanations (LIME) was introduced in 2016 by Ribero et al. [35]. In the pursuit of model-agnostic interpretability, LIME adopts a unique approach by perturbing the input and observing how the predictions change. The essence of LIME lies in approximating the black-box model locally, in the vicinity of the prediction to be explained, by constructing an interpretable model (e.g., a linear model with only a few non-zero coefficients). This is achieved by generating perturbations of the original instance, such as removing words or hiding parts of an image.

The key intuition behind LIME is rooted in the understanding that it is more suitable to approximate a black-box model locally than globally. This involves weighting the perturbed instances based on their similarity to the instance being explained. Consider the scenario of explaining predictions in an image. LIME transforms the image into interpretable components, such as contiguous super-pixels. A collection of manipulated instances is created by switching off certain interpretable components. For each perturbed instance, the model's prediction is obtained. A locally weighted, simple (linear) model is then learned on this dataset, prioritizing instances that possess a greater similarity to the original image. The produced explanation highlights the interpretable components that contribute most heavily to the model's predictions, simultaneously downplaying the prominence of less relevant features. The illustration of the LIME concept is presented in Fig. 3.

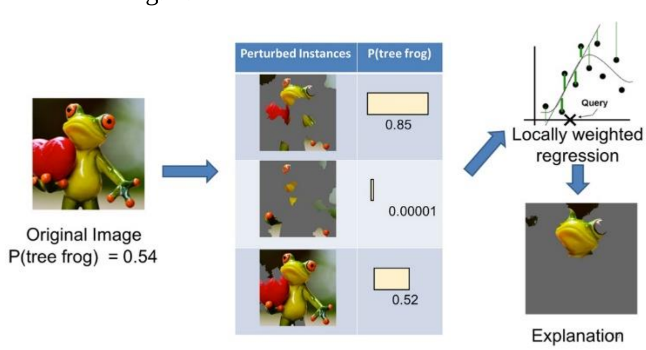

Fig. 3. LIME prediction explained by Ribero et al.

5) Occlusion sensitivity: Occlusion Sensitivity, as introduced by Zeiler and Fergus [36] in their paper on visualization techniques for conventional neural networks, is a method centered around systematically occluding or blocking individual regions of an input image to determine their influence on the model's prediction. The primary concept involves assessing how the probability score of the network changes when specific regions of the image are obscured.

By occluding various portions of the input image and observing corresponding shifts in the model's response, this technique facilitates the exploration of the model's reliance on particular regions or features for accurate predictions. If blocking certain areas significantly influences the model's accuracy, it suggests the importance of the occluded regions in the model's comprehension of the input. However, occlusion sensitivity might be computationally intensive, especially when evaluating multiple occlusions and it may not capture complex non-linear relationships.

6) Attention rollout: Similar to occlusion sensitivity, attention rollout offers a window into the decision-making process of ViT models. However, unlike occlusion sensitivity which physically blocks parts of the image, attention rollout delves deeper into the model's internal computations. Central to the functionality of ViT models are "attention" mechanisms, which enable the model to assign importance scores to various image regions. Attention allows the model to understand the relationships between different parts of an image, assigning importance scores to various regions. Attention rollout builds upon this by iteratively analyzing these attention scores.

Attention rollout starts with the final layer's attention maps, highlighting crucial image regions for the prediction. It then uses these maps to "roll back" through the network, revealing lower-level features (like edges or textures) that ultimately contributed to the final scores. By analyzing these intermediate maps, we gain insights into how the model builds its understanding of the image. Attention rollout offers advantages over occlusion sensitivity: it's computationally efficient and can capture intricate relationships between image regions. However, it doesn't provide a definitive explanation for the model's reasoning process.

III. Results

A. Studies of Scalp Disorder Diagnosis based on XAI and Deep Learning

Although the integration of DL and XAI has found extensive application in various healthcare research domains, its utilization in scalp imaging remains a gap in research. There is a clear necessity for additional research on the implementation of XAI in scalp imaging to advance its capabilities. As outlined in Table I, recent studies demonstrate a comparative analysis with conventional models, emphasizing the potential for enhancement and innovation in the domain of scalp disorder imaging. Table II illustrated Heng et al. research [37] based on two experiments. Tables III and IV display the results of the research conducted by Jeong et al. and Ha et al., respectively.

IV. Discussion

The Shih et al.'s seminal study [26] introduces a pioneering system for automated hair counting in scalp images, addressing challenges such as oily spots, wavy or curly textures, and overlapping hairs through a morphology-based approach, multi-scale line detection, and relaxation labeling. Their approach leverages a combination of techniques: morphology-based filtering, multi-scale line detection, and relaxation labeling. While evaluated on a limited dataset of 40 images, the system achieves remarkable results with an average precision of 98.0% and recall of 85.6%. Despite the limitations in data size and algorithmic complexity, this study represents a significant pioneering effort in the field of medical image analysis using ML. It paves the way for further advancements in automated hair analysis.

With more focus on telehealth as an application of scalp hair diagnosis, Su et al.'s study [3] introduces a system to automatically identify scalp conditions. The system offers potential benefits like faster diagnosis and utilizes a cloud platform for data collection and analysis, potentially improving accuracy over time. However, some limitations need to be addressed. The system focuses on surface-level conditions like dandruff and doesn't delve into potentially linked medical issues. Additionally, details about the training data used for the DL model are missing. Future work should explore incorporating analysis of potentially linked medical problems, increasing transparency in the system's decision-making process, and integrating with telehealth platforms for wider accessibility.

In a simultaneous effort, Wang et al. utilized a dataset comprising 1000 images, with 880 designated for training and 220 for testing. The scalp images were captured using a 200x magnification camera and categorized into four types of diseases. The researchers also introduced a novel model named ImageNet-VGG-f Bag of Words (BOW), which employ ImageNet-VGG pre-trained model[42] to evaluate its predictive capabilities in comparison to other ML classification algorithms. The achieved accuracy for this model was reported at 89.77%. This accuracy significantly outperforms other ML-based methodologies in the research, such as BOW with support vector machines (SVM) at 80.50% and pyramid histogram of oriented gradients (PHOG) with SVM at 53.0%. These findings underscore the promising potential of integrating hybrid DL approaches in the field of scalp hair imaging diagnosis over conventional ML methods.

Chang et al. introduced ScalpEye [2], a comprehensive system for scalp analysis that represents a significant advancement in scalp imaging. ScalpEye integrates medical imaging with AI analysis, offering a user-friendly mobile app for image capture, a cloud server for model improvement, a centralized platform for system management, and a portable microscope for high-quality image acquisition. The study utilized nearly 2200 scalp images from the COCO dataset, categorized into four common scalp conditions. Three deep learning models were employed for analysis: Faster R-CNN Inception_v2, SSD Inception_v2, and a novel model called Faster R-CNN Inception_ResNet_v2_Atrous. This new model combines Faster R-CNN with Inception_ResNet_v2_Atrous, which utilizes Atrous convolution for a stable receptive field size. This stability allows for better fine-tuning and more accurate predictions. Consequently, the Faster R-CNN Inception_ResNet_v2_Atrous achieved an impressive mean Average Precision (mAP) of 91.75%. While ScalpEye prioritizes both data quality and DL models within a cloud-based telehealth system, a key challenge remains. Annotating large datasets requires significant manpower and expertise. This raises the question of how the system will handle future large-scale datasets.

In Chow et al.'s research [38], the application of the CNN in the last run achieved an impressive accuracy of 96.30%. To gain a more profound insight into the factors that influence the model's classification of hair health, the researchers employed the LIME technique. Upon the analyzing of LIME, several observations were made. For instance, in the case of alopecia areata, a patchy bald condition, the heatmap coincided with the bald patches, although there were some inexplicable identifications in the right corner. The study concluded that despite achieving a remarkable accuracy of 96.30%, the application of LIME highlighted potential biases in the model's decision-making process, suggesting the need for further investigation and refinement. Further studies are crucial to identify and eliminate potential biases that could affect the model's biases and generalizability, potentially through image binarization and randomization techniques.

In the study conducted by Heng et al. [37], two experiments were conducted to assess the performance of dermatological image classification. The first experiment utilized the Dernet dataset, comprising 240 images with categories such as acne keloidalis, alopecia, and others. The second experiment involved a combination of Dermnet and Figaro-1k datasets[43], totaling 485 images, categorized as healthy and unhealthy. Two pre-trained models, Inception-v3[44] and SqueezeNet [45], using the RMSProp optimizer, were employed for these experiments. For the first experiment using Inception-v3, the model achieved an accuracy of 63.9%. In the second experiment, SqueezeNet was utilized, resulting in an impressive accuracy of 100%. However, despite this high accuracy, the integration of three XAI techniques, Grad-CAM, LIME, and occlusion sensitivity, revealed some noteworthy findings. In the second experiment, the classification was influenced by unrelated areas, casting doubt on the reliability of the 100% accuracy. On the other hand, the first experiment suggested that the model's predictions were primarily affected by the forehead area, highlighting the importance of specific regions in making final decisions. However, despite this emphasis, the accuracy achieved was only 63.9%.

TABLE I. SUMMARIZING AI STUDIES IN SCALP DISORDER DIAGNOSIS

Article	Dataset	Model	Results
Shih et al. (2015)[26]	40 scale images	Hair-bundling algorithm	98.0% of precision 85.56% of recall
Su et al (2018)[3]	Not mentioned	VGG-net	90.9% of accuracy
Wang et al. (2018)[4]	1000 images (880 training images/ 220 testing images)	ImageNet-VGG-f model Bag of Words	89.77% of accuracy
Chang et al. (2020)[2]	2198 images	Faster R-CNN based model	91.75% in mAP
Chow et al. (2022)[38]	1079 images (864 training image, 215 validation image)	LIME, CNN	96.63% of accuracy
Heng et al. (2023)[37]	DermNet dataset: 240 images Figaro-1k dataset: 245 images	Integrating Grad-CAM/LIME/Occlusion Sensitivity with multiple DL models	Illustrated in Table II
Jeong et al. (2023)[39]	100,000 images (x60)	EfficientNet-B6	Illustrated in Table IV
Roy et al. (2023)[40]	150 images	CNN	91.1% of accuracy
Ha et al. (2024)[41]	100,000 images (x60)	Attention rollout with ViT-B/16	Illustrated in Table III

TABLE II. HENG ET AL. RESULT [37] BASED ON TWO EXPERIMENTS

Scalp Symptoms	Number of images	Accuracy (%)
Dryness	17,434	91.3
Oiliness	80,416	90.5
Erythema	4,592	89.6
Folliculitis	4,592	87.6
Dandruff	40,482	87.3
Hair loss	25,682	89.0

In Roy et al.'s concurrent research [40], a dataset comprising scalp images from multiple sources was collected, consisting of 150 images depicting three different diseases: alopecia, psoriasis, and folliculitis. The research employed CNN, and after experimenting with 25 different combinations, a neural network architecture with three hidden layers, one input layer, and one output layer was chosen as the final design. The training process used a batch size of 16 for each batch over 50 epochs, and the preprocessed data was divided into a 70-30 train-test split for training and validation purposes. The model was constructed with 256 inputs, a 3x3 square kernel, 3 output units, and a Softmax output layer. The model achieved a training accuracy of 96.2% and a validation accuracy of 91.1%. This approach demonstrates a careful exploration of model architecture variations, leading to the selection of an optimal configuration. The high training and validation accuracies indicate the effectiveness of the chosen model in learning and generalizing from. However, it is essential to consider the potential impact of overfitting and the model's performance on unseen data.

TABLE III. RESULTS OF JEONG ET AL.'S RESEARCH UTILIZING EFFICIENT NET-B6 MODEL

Dataset and Model	DermNet and Inception-V3	Figaro-1k and SqueezeNet
Training accuracy (%)	98.4	100.0
Validation accuracy (%)	63.9	100.0
Validation sensitivity (%)	88.9	100.0

TABLE IV. RESULTS OF HA ET AL.'S RESEARCH UTILIZING THE VIT-B/16 MODEL

Scalp Symptoms	Number of images	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)
Dryness	17,434	77.7	76.7	77.0	76.9
Oiliness	80,416	69.0	70.1	69.7	70.6
Erythema	4,592	81.4	81.6	81.5	81.7
Folliculitis	4,592	82.3	82.5	82.3	82.6
Dandruff	40,482	77.1	79.3	79.3	79.3
Hair loss	25,682	82.3	83.1	83.0	83.0

AI-ScalpGrader [39], a DL system designed for scalp diagnosis, offers promise with its detailed classification scheme. Analyzing ten scalp conditions based on seven dermatologist-defined indices, it provides a more comprehensive picture of scalp health compared to limited-scope systems. Additionally, the cloud-based platform facilitates data storage, analysis, and potentially allows remote monitoring of scalp care. However, limitations exist. The system's accuracy, reported to be between 87.3% and 91.3% for various scalp conditions, depends heavily on training data quality and diversity. While a sizeable dataset of 100,000 images is mentioned, details regarding its composition and potential biases such as: F1-score, recall and precision are lacking. Transparency surrounding the verification process is also needed to build trust in the system's reliability. Expanding the training dataset with a wider range of scalp conditions and ethnicities is crucial. Additionally, exploring integration with telehealth platforms could revolutionize access to scalp care services.

One of the latest studies presented in Ha et al.'s research [41] proposes a DL-based intelligent healthcare platform to diagnose six common scalp hair disorders (dryness, oiliness, erythema, folliculitis, dandruff, and hair loss) with the same dataset as Jeon et al.'s study [39]. Distinguishing itself from prior research, this platform not only classifies the presence or absence of a condition but also predicts severity levels ranging from 0 to 3 for each disorder. The study advances the field by encompassing a broader spectrum of scalp conditions, incorporating predictive severity assessment, and integrating XAI techniques for lesion visualization. Moreover, its user-friendly software facilitates convenient self-monitoring at home. However, the authors acknowledge the potential influence of lighting environments on data quality, particularly affecting the classification of oiliness severity. Overall, this study underscores the promising potential of DL and XAI, notably ViT models and attention rollout, in the analysis of scalp health, although further research is imperative to ensure widespread clinical adoption.

In summarize, the pursuit of effective methodologies for scalp imaging and hair disorder diagnosis has led to the establishment of multiple research initiatives. DL techniques have outperformed traditional ML approaches in terms of accuracy, efficiency, and generalizability, showcasing their potential in advancing the field. Nevertheless, the inherent opacity of decision-making processes in DL poses challenges for clinical applications. The integration of XAI techniques, such as LIME, Grad-CAM, SHAP and attention rollout presents promising avenues to address this issue. However, a critical need for further research exists to comprehensively understand how these DL methods interact with wider range of datasets, ensuring their efficacy and reliability in real-world clinical scenarios.

V. Conclusion

In conclusion, our comprehensive review of studies underscores the transformative impact of DL in revolutionizing scalp imaging and advancing the diagnosis of hair disorders, especially with the help of XAI in understanding complex decision-making process. The demonstrated synergy between XAI and DL in handling complex imaging tasks marks a significant advancement. However, the imperative for ongoing research in this domain is encouraged, with the possibility to improve treatments for this global concern. The combination of XAI and DL holds promise not only for professionals but also for non-professionals, offering potential applications in self-diagnosis. Looking forward, the pursuit of further research, particularly in real-time detection, stands to benefit both professionals and individuals, contributing to improved living conditions for those affected by hair scalp diseases. However, several limitations remain. Many studies rely on small, non-representative datasets, limiting generalizability, and the lack of transparency regarding training data raises concerns about potential biases. Additionally, while XAI techniques like LIME, Grad-CAM, and SHAP provide valuable insights into model decision-making, they add computational complexity that may hinder clinical adoption. Some models demonstrate strong performance under controlled conditions but struggle in real-world settings due to variables like lighting and image quality. Moreover, the integration of these systems with telehealth platforms and their ability to predict severity levels across diverse patient populations still require further refinement. Despite these challenges, the combination of DL and XAI offers significant potential for improving the diagnosis and treatment of scalp and hair disorders, but further research is crucial to ensure their efficacy, transparency, and widespread applicability in clinical practice.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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