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Original Article

Computer Imaging of Alopecia Areata and Scalp Detection: A Survey

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Abstract *- Alopecia Areata (AA) is a frequent inflammatory affliction that causes erratic Hair Loss (HL). As with other resistant-influenced disorders, the development of AA is assumed to be the result of a complicated balance between surroundings and heredity. Various factors can cause hair loss, and trichoscopies and biopsies are usually required to ensure the cause of AA. There is currently no remedy for AA, although doctors can recommend various medications to support hair regrowth rapidly. AA does not immediately cause illness and is not communicable, but it is tough to adjust psychologically. Further, many people's experience with AA is regarded as a terrible infection that needs counselling for the mental and physical components of HL. So, an efficient HL detection system should be developed to tackle this emotional perceptive. Detecting the AA detection with scalp condition is required to find out the cause of AA level and can provide guidance for proper treatment. Computer vision using deep learning techniques is gaining significant attention because of improved performance over previous approaches. This article presents detailed analyses of different AA detection approaches using (Artificial Intelligence) AI techniques with modern Deep learning. First, AI-based frameworks designed by researchers in the past for different AA are studied briefly. After that, a comparative study is conducted to understand those frameworks' drawbacks and suggest new solutions to improve the AA detection system.*

Keywords *- Artificial Intelligence, Alopecia Areata, Hair Loss (HL), Scalp Condition, Detection System.*

1. Introduction

Hair is an important part of a person's appearance and may greatly influence their perceived attraction and identity. On the human scalp, 100,000 to 350,000 hair follicles go through cyclic stages of development. The frequency of the hair growth cycle is affected by age, disease, diet, and physiological characteristics. HL, also known as baldness, is a natural source of aging. There are two categories of HL, focal and diffuse, each with many underlying causes [1]. Table 1 presents the various kinds of HL and their characteristics, whereas Table 2 presents their causes.

Table 1. Varieties of HL and their Characteristics

HL category	Unique characteristics
Diffuse HL	
Women pattern HL	hair thinning is one symptom; unbroken hairline in front; a no-pull test
Men pattern HL	Hair loss is a symptom. ; M type pattern; negative pull test
Diffuse AA	Patchy Distribution; the positive pull test
Alopecia Universal (AU)	Total Hais Loss on the scalp and body
Telogen effluvium	30%–50% HL Positive pull test three months after the inciting incident
Anagen effluvium	2 weeks after chemotherapy, HL of up to 90% occurs suddenly.
Focal HL	
Non-scarring AA	Exclamation point hairs surround the usual scalp.
Tinea capitis	A potassium hydroxide investigation revealed a scaly scalp with fungus.
Traction alopecia	Patchy; may be scarred; may be related to hair habits.
Trichotillomania	Scarring and psychological distress are possible.
Scarring alopecia	Scalp scarring and thinning (e.g., discoid lupus erythematosus)

Table 2. Causes of Different Kinds of HL

Diffuse HL	Focal HL
1. Telogen effluvium (e.g., after disease or stress) 2. Anagen effluvium (e.g., after chemotherapy or radiotherapy) 3. Drugs	1. AA (possibly autoimmune) 2. Cicatricial (scarring) alopecia (e.g., lichen planopilaris, discoid lupus erythematosus, folliculitis decalvans) 3. Traction alopecia (e.g., improper hair ironing and braiding)

4. Imbalanced vitamin (micronutrient) 5. Hair diagnosis 6. Androgenetic alopecia (in females) 7. Hormone variations (e.g., Menopause, cessation of oral contraception, hypothyroidism)	4. Trichotillomania (hair pulling) 5. Scalp infection (e.g., ringworm)

Many persons who lose their hair will suffer a few levels of psychological stress. For example, most people who have HL after radiotherapy believe that it is the most harmful consequence of the treatment. One of the most common forms of HL is non-scarring AA, defined as acute HL without cutaneous inflammatory signs [2-5]. This disorder normally initiates unexpectedly with one or many patches that increase centrifugally. AA influences people from all backgrounds, ages and gender, with a survival rate of 1.7% in the normal community. Pediatric AA accounts for approximately 20% of all AA patients, with more than 50% of patients experiencing their initial incident before age 20. Figure 1 portrays the effects of AA on the scalp.

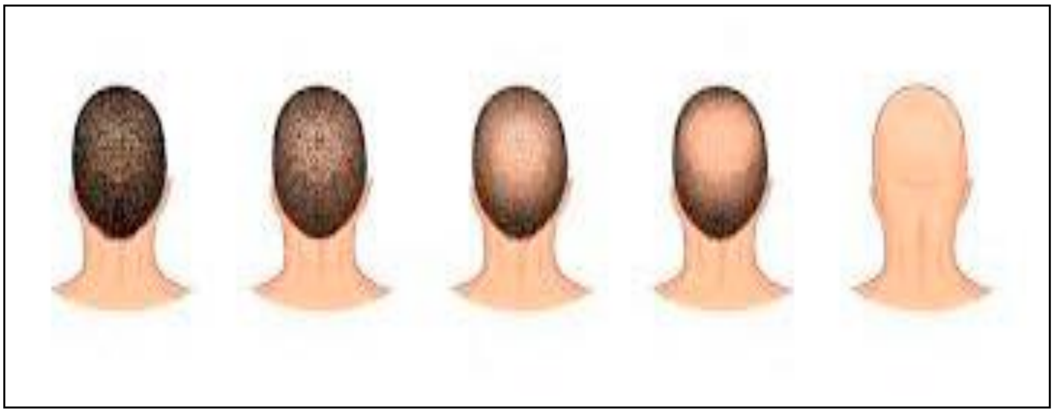

Fig. 1 Effect of AA on Scalp

There are 3 kinds of AA, as illustrated in Figure 2. Two to three HL patches on the scalp characterize AA. Alopecia Totalis (AT) is a condition in which the scalp is completely bald. AU is characterized by whole-body baldness. Patients with AT or AU, according to the majority of research, are more likely to be affected by poor diagnosis and treatment.

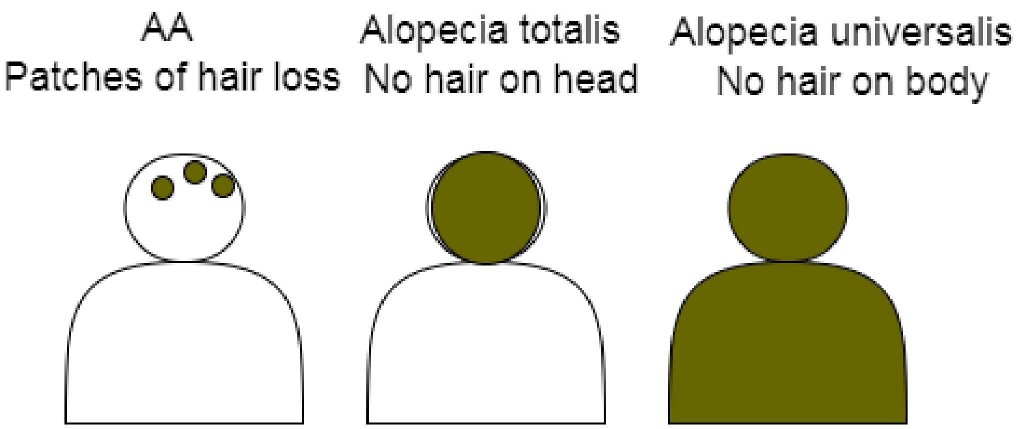

Fig. 2 Categories of Alopecia

Due to its abrupt onset and unexpected progress, AA has a significant psychological effect. In reality, the treatment of this condition is highly unpredictable because of the unknown cause and the involvement of various harmful conditions. According to studies, 34-50 percent of patients will recover within a year, but 15-25 percent will seek complete scalp HL or hair loss from the entire scalp and body, which has a 10% chance of being detected treated successfully.

Many image processing approaches have been utilized in dermatology to recognize and diagnose AA with the help of trichoscopic images [38-39]. In advanced medical fields, trichoscopy has been utilized to diagnose a patient's scalp condition accurately. Trichoscopy is a rapid, non-invasive, and cost-effective at-home approach for obtaining critical physical diagnostic information to aid in the proper diagnosis of alopecia areata. Table 3 summarizes a few image processing approaches available in the detection and diagnosis of AA over the past decades.

Table 3. Some of the Image Processing Approaches for AA Detection and Diagnosis

Approaches	Description
Acquisition of Images	The process of extracting a digital image from a physical source, such as trichoscopy, microscopy, USBmicroscopy, etc.
Grayscale conversion	The process of transforming a multi-channel or colour digital image to a single-channel image with a single intensity value for each pixel.
Background image extraction	Separation of the image background, retrieving foreground objects.
Image enhancement	Improvement in the perception of image details for human and machine analysis.
Image histogram analysis	Pixel plot analysis in terms of peaks and valleys formed by pixel frequency versus pixel intensities.
Binary image segmentation	Foreground objects separate from the background in a binary (black-and-white) image.
Color image segmentation	Image objects separated in a color image, regions of interest.
Image filtering	Process of distorting an image in the desired way using a filter.
Feature extraction	Defining a set of features or image characteristics that efficiently or meaningfully represent the information important for analysis and classification.

On the other hand, these detection and diagnosis using image processing approaches for AA have minimal success rates; no cure has been discovered, and no therapy has been proven effective in preventing illness recurrence. Diagnosis possibilities are topical, locally injected, or systemic steroids; topical immunotherapy; topical minoxidil; topical irritants like anthralin; and systemic immunosuppressants like cyclosporine or methotrexate. The success rate varies according to the severity and frequency of the illness. As this often disfiguring condition can be psychosocially stressful, psychosocial assistance and treatment are also crucial for disease care.

From this perspective, there is a lot of scope for innovative AI methodologies in detecting and diagnosing AA. Machine Learning (ML) approaches, and their advanced variants have demonstrated efficacy in the Trichology field in detecting and diagnosing various scalp disorders or symptoms. Scalp hair images have been utilized to recognize the scalp conditions and AA with the help of ML approaches, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and decision trees [8-10]. Conversely, the accuracy of these approaches is hard to determine when they are used without any physician input. One significant shortcoming of ML is that it is difficult to describe how these approaches reach their findings. The ML approach is analogous to a black box that accepts inputs and creates outputs without explaining how it did so. If an approach incorrectly detects an AA, it cannot explain why it chose that particular diagnosis. While the outputs can be useful, if the model cannot explain to a patient why it classified a scalp symptom as AA versus healthy or recommended a specific treatment, it is potentially harmful and troublesome for the patient. To explain why a diagnosis or therapy should be adopted, a physician's interpretation is required. Also, these approaches are easily prone to overfit, and if the scalp images are poorly labeled, then the approach's outcomes will reflect inaccuracies.

To combat all these challenges, Deep Learning (DL) approaches, including Convolutional Neural Network (CNN) and its variants, have emerged in the Trichology to recognize and diagnose the AA properly [11]. The detection and classification of images through CNN has gained the most attention for its potential to increase the accessibility of scalp conditions or AA screenings and streamline the workflow of trichologists. CNN has already proven successful in many other fields such as ophthalmology, pathology and radiology.

1.1. Research Gap

Patchy, AT and AU are the traditional classifications for AA. A more comprehensive categorization should consider the period of the illness and, in the case of patchy AA, the degree of hair loss. Ophiasis, involvement of sites on the trunk and limbs, the beard and eyelashes, and nail illness should all be emphasized in the pattern description. The Severity of Alopecia Tool (SALT) score, a rating system based on these characteristics, has been developed to solve this problem. There was the development of an AA advancement indicator using a four-quadrant division of the scalp surface. Based on clinical symptoms and the amount of hair loss, hair loss in each quadrant was graded. AA is often diagnosed based on clinical findings, and no additional testing is required. Also, other systems, like dermoscopy or histopathology, can support the diagnosis.

There isn't much consensus in AA over a classification scheme. It restricts the capacity to precisely and methodically evaluate and record the severity of AA among patients. Further, AA categorization will be crucial in guiding treatment recommendations as targeted medicines for AA become more prevalent. It will be crucial to have a broader understanding of AA severity to match therapies with patients. Additionally, considering AA's severity beyond the degree of scalp hair loss acknowledges the disorder's high mortality.

1.2. Problem Description

The study shows no research has been done using hair pictures to identify and categorize AA. Previous research has used scalp and dermoscopic pictures. Also, various machine learning techniques have made effective diagnoses and predictions in dermatology. Systems for classifying scalp photos have been created using SVM and KNN. Scalp pictures from machine learning have been used to categorize ailments like dandruff using SVM, KNN, and decision trees. These methods create prediction models using photos of the scalp and skin. To our knowledge, no machine learning algorithms have yet been used on photographs of human hair. So, this survey helps to address the problems in the AA classification and recommends solutions to enhance the efficiency of AA diagnosis.

The main goal of this manuscript is to present a complete survey of various AI techniques for detecting AA. Also, a comparative study is presented to address the advantages and limitations of those techniques to suggest future scope for AA detection. The remaining sections of this manuscript are structured as follows: Section 2 discusses various AI techniques developed to detect AA (e.g., HL and scalp conditions). Section 3 illustrates the comparative analysis of those techniques, while Section 4 discusses the inferences. Section 5 concludes the entire discussion.

2. Survey on Alopecia Areata Classification Techniques

The reactive scalp intensity and clinical features were evaluated using the new score (3s) procedure [12]. A public questionnaire was performed in this technique that included the French populace aged between 15 and above. Poll respondents were questioned over the telephone and chosen using an allocated system like gender, age, occupation of household head, type of geographical area and region. By contacting back 20% of the respondents, a comprehensive audit of the conversations was done. If this approach indicated an odd finding in a particular inquiry, all discussions performed by the implicated investigator would be carefully reviewed. When the questionnaire items are considered, the appearance of responsive scalp and its intensity and presence of a scalp disorder (HL, seborrheic dermatitis, psoriasis, allergy, or others), the emergence of stiffness, incinerating, tickling sensation, itchiness, or anguish feelings on the scalp and the struggles that these feelings stimulate, and the incidence of other diagnoses (free answer) are witnessed. However, it is quite impossible to see respondents behind the hair, and there is no way to evaluate the delicate scalp accurately.

An Artificial Neural Network (ANN) method was developed [13] to predict and diagnose HL. The quantity of HL was affected by parameters like age, gender, hereditary details, maternity, medical history, zinc insufficiency, iron deficit and aesthetic usage in this approach. This method's database was generated through physician consultations and the implementation of precise clinical test results. In one year, the information was gathered from people and with the cooperation of clinicians and professionals. These parameters were used as input variables to ANN to identify the quantity of HL. However, this method has acquired less convergence speed.

An Unsupervised Hair Segregation and Counting System was developed [14] using Microscopy Images. This technology was intended to create health programs for diagnostic applications by utilizing sophisticated visual multi-sampling algorithms. This strategy was adopted to tackle three important concerns with hair segregation and enumeration. First, remove any bright spots caused by oil or moisture, which creates concentric designs in the center of the scalp hair and considerably affects the boundary's correctness. Second, two touching or overlaying hairs were identified and categorized as a single hair. A hair-bundling technique was created to compute any hidden hairs to address these challenges. Finally, hairs might be frizzy or twisted, rendering the traditional Hough-based line recognition method inappropriate due to parameter settings such as the minimum size of the vertical line and proximity among parallel lines. However, this method has more blurred and noisy images.

The correlation of trichoscopy observations in AA [15] was developed to evaluate infection prevalence, duration, and diagnostic category in Turkish patients. White spots, manifold-hair follicle cells, concealed strands, and black speckled colouration in the scalp areas are all early signs of AA. In unclear situations, a checklist of AA individuals was applied for trichoscopy observations by employing clinically confirmed and validated scalp dissection. SPSS 15.0 was used for quantitative assessment. The proportions of qualitative factors were determined and evaluated using the $\chi 2$ test. To identify the predicted variables, a logistic regression model has been used. The odds percentages were determined using descriptive statistics to evaluate the trichoscopy results. However, the lack of histological validation of several novel symptoms and the small number of participants were considered the limitations.

AA Progression Index (AAPI) was established [16] to assess entire HL conditions in AA patients based on trichoscopy observations linked with AA activity. The outer layer of the follicle regions was split into 4 segments. The proportion of alopecic region, diagnostic indications linked with HL, was employed to evaluate HL conditions in the entire portion. This AAPI approach was used to increase the heterogeneity of the SALT score. However, this system has a smaller sample size and high classification error.

Using a low-cost microscope camera, an effective technique for automatically analyzing hair and scalp conditions was created [17]. Initially, the three critical features like hair volume, width, length and scalp patch were extracted from the hair (Microscopic) image. Then, a chronological analysis was done on the acquired attribute data to measure the client's hair and scalp affliction. To improve the accuracy of feature extraction, the features were pre-processed and then the scalp blotch detection method was used to detect the blotch region on the scalp. The accuracy of the definite hair width was measured using a digital microscope. Finally, this counting algorithm was performed for the scalp images dataset. However, this scheme has more noise and a blurred spot in the image, affecting the detection performance.

The dimension, spiral rating, and pulse amplitude were used to produce the geometric categorization of scalp hair curled types [18] for reliable medication screening. After receiving moral permission and explicit agreement, 48 balanced individuals with distal virgin (6cm) hairs collected from the apex of their scalp were examined. For the 8 and 6-group categories, three observers each rated hairs from 48 participants twice. One observer used the 6-group categorization on 80 consecutive participants to validate the system's dependability. To measure Intra and inter-rater contracts, the Kappa measure was utilized. Also, the operator error can be reduced by using a digital classification system. However, this method was not up to the mark compared to other existing methods.

Lengthy-term tofacitinib therapy for extreme AA, Alopecia Totalis (AT), and Alopecia Universalis (AU) was indicated [19] in a sequence of individuals over a prolonged duration of a period. Every patient's medical and epidemiological analysis was conducted, particularly age, gender, illness beginning age, length of the present phase of the condition, genetic factors, and AA intensity as determined by the SALT. While starting tofacitinib medication, all participants should have a preliminary test, which includes a total plasma cell count and HIV, hepatitis B and C virus screenings. Images were captured before the start of therapy and during the eventual clinical sessions. These photographic images were utilized to measure condition intensity and treatment response. The SALT score was used to quantify the HL by using efficacy. However, the technique's limitations include the prospective structure of the information, the comparatively small proportion of individuals, and the absence of a reference subject.

A controlled, non-contact, non-aseptic optical technique for detecting fungal sepsis on the scalp was devised [20] to prevent HL difficulties. The automated scalp characterization used characteristics from A-line and B-scan images of Optical Coherence Tomography (OCT). The collected characteristics using OCT images were then used to train an ML multi-layer ensemble model. Finally, the algorithm provides a potential technique for scalp characterization, presenting concrete data in healthy and fungal-infected scalps using analytical methods. However, this approach has a considerable temporal intricacy.

An automated scalp evaluation and diagnostics method for hair scalp condition was constructed [21] Based on DL methods. This technology may detect the condition of the patient's scalp autonomously. This approach comprises a scalp detector, tablet software, and a cloud administration network. The scalp monitor was linked to the tablet through the Wi-Fi module. The designed detector would collect and analyze the scalp image. The tablet transmitted and displays the identified scalp finding. This approach would accurately evaluate the information on the scalp, such as germs, allergens, seborrheic dermatitis, sebum, and HL. In using a cloud management system, loss of data might have resulted.

The scalp state detection method was developed [22] using ML methods like ImageNet-VGG-f model Bag of Words (BOW) and pyramid histogram of oriented gradients (PHOG) classifiers. This procedure was created for those with many hairy scalp lesions due to professional stress, excessive working periods, and a shortage of scalp hygiene, among other things. At first, scalp images were captured as original data and pre-processed to extract critical properties such as hair color, brightness, and thickness. The pattern recognition approach was then utilized to identify the relevant areas in the images. The classification trainer apps were suggested for healthy scalp visual screenings. The data enhancement approach was used to balance the number of images in the categorization. On large datasets, this method provides low classification accuracy.

A simple hair and scalp self-diagnosis embedded system was implemented [23] using webcam and microscope sensors to extract characteristic images of the hair and scalp status of the user. An image processing technique was applied for pre-processing and feature comparison to determine the hair and scalp status of the patient. The scalp was photographed under unknown lighting conditions from the collected scalp data. Therefore, the SVM was employed to predict the lighting conditions using the differences in the colors of the images so that different environments could adjust the parameter. Therefore, in this work, the Norwood-Hamilton scale model was used as a reference for users to utilize the golden phase for treatment. However, this method has high time complexity.

A digital imaging technique [24] was employed to reproduce the SALT score system for evaluating AA conditions. Texture analysis was utilized to discriminate among natural hair and bald scalp in a pediatric AA image collection of four interpretation images. An instance lay of textured hair was obtained from severity variances over a low-resolution patch, and it was utilized to provide a wider perspective and enhance dispersion of all independent images into regions of various hair intensities by capitalizing on local image metrics and the familiarity of hair feature differences throughout neonatal alopecia instances. This technique replicates a SALT and may offer further data on the evolution of hair volume alterations reported in AA. However, this method has high computational complexity.

A Feed-Forward ANN (FFANN) and back-propagation (BP) method was developed [25] to detect the alopecia disease. The algorithm was entirely constructed on the AA ailment dataset. This presented system would find out earlier alopecia signs by using an FFANN. The FFANN discriminated against the collected data based on the features. Then, the subject was classified into the sections of healthy or unhealthy patients. The FFANN performances were evaluated using the learned features to distinguish between healthy and affected patients. This model might be valuable for medical experts who want a different perspective because of the constant pattern of apparent indications. However, this method could be acquired with highly noisy data.

The topographic phenotypic expression of AA was discovered [26] by utilizing aggregate scoring to develop a predictive framework and ranking structure for categorizing illness prognostications. The tree-based technique was designed to grade AA items. A prognostic prediction method was constructed for differentiating ailment probability in patients with AA, with group selection based on topographic characteristics generated from clustering scrutiny of sectorial information. Furthermore, the tree model of the aggregate technique was translated into the Topography-based AA Severity Tool (TOAST) for defining the topographical features and diagnosis of HL in AA cases. However, the sampling error was high in this model.

The DL method was investigated [27] for discovering HL levels for the male gender using facial images. This technique generated a different trained sample of facial images with varying degrees of baldness. Different CNN networks, such as Kaggle-CNN, DEX-IMDB-WIKI, and DEX-ChaLearn Networks, were employed in this approach to determine the semantic interpretation of facial images by determining their most relevant properties. Furthermore, a matching approach for autonomous recognition of face scans with relation to pattern categorization of male phalacrosis offered by the medical profession was developed. However, this system has resulted in overfitting problems.

A comprehensive simulation-based meta-analytical framework was developed [28] for predicting biological indicators in AA based on differential expression analysis, systems biology, and functional proteomic research. This analytical approach was used to find epigenome associations in alopecia and HL by analyzing microarray datasets and putative candidate molecular markers such as extracellular peptides from a list of alternatively transcribed genes. In route evaluation, physiological events such as protein metabolism and signal propagation were employed to highlight their importance. These pathways are responsible for hair growth, hair follicle development, pigmentation, and morphogenesis. However, more theoretical studies based on molecular analysis should be done for efficient results.

An approach was suggested [29] for avoiding HL and scalp self-diagnosis by retrieving an HL Feature (HLF) from scalp images captured with a microscope utilizing grid line sampling and Eigenvalue. The photographed scalp scans were pre-processed using a pre-processing image approach to optimize the microscope source quality and reduce specular lighting. Using the pre-processed scalp image, the HLF was then retrieved using a different technique to determine the HL progress degree. Finally, HLF was described as the number of hairs, hair follicles, and hair thickness that combine damaged strands of hair, small vellus hairs, and draining hairs. This approach was selected to determine everyone's scalp by attaching a USB microscope to accessible equipment such as a digital wristband or a mobile phone and adjusting techniques to simplify the calculation of all pre-processing procedures. However, this approach was not carried out correctly due to the entry of the pre-processing image.

Image processing algorithms were developed [30] to provide a pre-trained categorization assessment of scalp diseases. The scalp image was initially pre-processed utilizing image enhancement and greyscale conversion methods. Following that, three characteristics from all input images were extracted and saved in a Region of Interest (ROI) database. The pre-classified attributes were used as a guideline in the categorization procedure. Using the SVM technique, this method classified three forms of scalp diseases: AA, dandruff, and normal. Sometimes, the SVM algorithm might underperform for an excessive number of training data samples.

A DL-based intelligent scalp examination and a diagnostic system called ScalpEye were introduced [31] to establish an effective scalp hair physiotherapy system as part of scalp healthcare. The ScalpEye device could detect and diagnose 4 main scalp hair ailments: flaking, folliculitis, HL, and greasy hair. This system comprises a compact scalp hair imaging microscope, mobile apps, a cloud-based AI training platform, and a cloud-based administration framework. For evaluating and assessing scalp hair problems, a Faster R-CNN (FRCNN) with an Inception ResNet-v2-Atrous module was used in conjunction with the ScalpEye system for visual identification. However, this method has high time complexity.

Clinically Applicable Deep Neural Network (DNN) was reported [32] to calculate the SALT rating for recognizing the scalp region and HL in AA patients. Using pattern inspection, a statistical approach for detecting AA lesions was created by evaluating pre-trained scalp images. Furthermore, this approach does not necessitate time-consuming image processing because it can calculate the scalp region from an unprocessed input image. It does not necessitate any stringent action in obtaining clinical images. However, this paradigm has limited generalizability. However, this model has limited generalizability.

An effective, non-invasive bio-engineering technique [33] was proposed to report each hair follicle production using a significant variety of HL patients' concerns. Hair productivity in this technique includes thickness, length, and increased daily hair rate. Then, transverse research for hair production in female and male patients was created using self-evaluation of HL, Contrast-Enhanced Phototrichogram with Exogen Collection (CE-PTG-EC) and Scalp Coverage Scoring (SCS). Finally, monitoring the production of actual hair follicular units during medication trials from persistent investigations was induced. However, in contrast to the rigorous analytical procedure, modest variation in SCS was discovered because the physician focuses on the worst damaged locations.

A framework was developed [34] using hair images for classifying healthy hairs and AA. The features extraction method was used to extract color, texture, and shape. Image pre-processing techniques like enhancement and segmentation were applied to remove any unwanted deformation from the hair images. After that, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classification techniques were utilized to develop an ML network with 70% of the images, with the remaining image set employed for validation. Consequently, the AA and normal hairs were categorized. However, this strategy has the constraint of using ML algorithms on a limited sample with no medical evidence.

The menace prediction of AA moving to AT and AU was found [35] using bio-label development with proteomics Analysis and ML system. Proteomics analyses were performed to identify important genes co-related to AU to AT based on the entire genomic activity of human scalp epidermal biopsies samples. Then, based on the main genes identified through computational analysis, a bio-label was created utilizing several ML algorithms. However, this technique requires larger datasets for efficient performance.

An expertise approach was developed [36] to help clinicians diagnose patients with various HL illnesses. This system does not require considerable experience because it was created with the Clips programming language. This approach was intended to support physicians in diagnosing HL diseases, including seborrheic psoriasis, lichenoid keratosis, Tinea, AA, thyroiditis, and Androgenetic alopecia. This Clips Expert System language was employed for designing and implementing this expertise model. However, this expert system focused solely on disease diagnosis and could not diagnose the disease if more than one symptom of different diseases was selected.

Advanced Hair Density Measurement (HDM) utilizing DNN was created [37] for entity recognition and describes the possibility of automating HDM. The corpus for learning and examining this system might consist of distended hair scalp RGB images acquired from male HL patients, as well as the respective notation data, which enclosed details about the position of the hair follicles in the scan reports and follicle-type information based on the number of hairs. The object recognition methods EfficientDet, YOLOv4, and DetectoRS were employed for comparative results. However, this method does not contain a sufficient number of training datasets for an automated HDM.

3. Comparative Analysis

This section presents a comparative analysis of AA disease detection using different AI techniques studied in the above section regarding their merits and demerits, whose technical details are studied in the above section. In Table 4, both merits and demerits of the above-studied techniques used for AA detection and diagnosis are investigated. The best solution is suggested to overcome those drawbacks in detection to obtain better accuracy.

Table 4. Comparison of the performances in different AI-based techniques for AA disease detection

Ref. No	Techniques	Merits	Demerits	Performance Metrics
[12]	New score (3s) system	This method has been suitable for all age groups.	It's tough to assess people beneath the hair, and there's no way to describe an attuned scalp accurately.	The average 3S was varied in these three populace: 1.69 (±1.76) for subjects with a slightly sensitive scalp, 2.06 (±1.89) for moderate scalp conditions and 3.53 (±3.39) for more delicate scalp
[13]	ANN	Less computational burden	Less convergence speed	Levenberg- Marquardt has considered this technique's deviation in 19 epochs = 0.0348 and MAE = 0.1393.

[14]	Hair-bundling technique, Hough-based line recognition and unsupervised learning	Less time complexity	More blurred and noisy images.	Precision = 98.05% Recall = 85.56%
[15]	Correlation of trichoscopy observations	This method has innovation toward trichoscopy findings in alopecia areata	Absence of confirmation of some new signs histopathologically and the low number of patients	-
[16]	AAPI score	The performance was statistically reliable	Smaller sample size and high classification error	The percentile AAPI for all patients in the first and second evaluation phases varied from 7.2 to 198.9 and 70.4 to 122.9, respectively.
[17]	Features extraction, Scalp blotch detection and hair counting algorithm	It is a simple method with good detection accuracy than other conventional methods	More noises and blurred spots in the microscopic hairy image	Accuracy = 94.90%
[18]	Kappa measure and digital classification system	High generalizability system	Detection accuracy was less than other existing methods	Cross concordance for the 8 groups' geometric rating was 0.537; for the 6 groups, the geometric rating was 0.728.
[19]	SALT score	Low computational cost	This technique includes the prospective data quality, comparatively limited number of patients, and the absence of a regulated cohort.	SALT score for patients with AA patients = 81.9%; and patients AT or AU =59%
[20]	Multi-layer ML ensemble model	High generalizability system	High-time complexity issues	Average sensitivity = 92.30 , specificity = 90.90 and Accuracy = 91.66%
[21]	VGG-Net	Less computational complexity	Data Loss might occur due to the cloud management systems.	Accuracy = 90.9%
[22]	ImageNet-VGG-f model BOW and PHOGs classifier	This approach could effectively identify features in an image at various scale measurements.	Low performance on large datasets.	Accuracy of BOW with SVM = 80.50% and PHOG with SVM = 53.0%
[23]	Otsu threshold, K-means clustering SVM and Norwood-Hamilton scale model	This method has a simple design and a fast diagnosis system.	High time complexity	Accuracy for oily scalp = 71%; Accuracy for allergic/red and swollen = 84% Accuracy for dry and cuticularized = 78%
[24]	Gibbons approach, K-means clustering and SALT score	The algorithm effectively distinguishes normal and bald scalp and lower-density hair patches.	High computational complexity.	Average errors for SALT score = 31% ; Average featuring = 60%; Average frame match = 59%
[25]	FFANN and BP strategy	Less time complexity	Might Acquire highly noisy data.	Resulted classification accuracy = 91%

[26]	Cluster analysis and tree-based algorithm	High reliability which might easily be applied in clinical practice	High sampling error	The predicted accuracy for the high degree of predictability when it comes to allocating cases to groupings = 94.7%,
[27]	Kaggle-CNN DEX-IMDB-WIKI and DEX-ChaLearn	If properly initialised, this structure might be trained using more facial images from the sources.	This system might have an overfitting problem	Average accuracy (%) of like Kaggle-CNN = 82.5%; DEX-IMDB-WIKI = 85.5% and DEX-ChaLearn = 84.5%
[28]	Normalization, Robust Multi-array Analysis (RMA) and gene ontology	This strategy was useful for identifying mutations in sequential information to boost the novel bio-labels detection for comparable conditions.	More theoretical knowledge of the molecular study was required	As per ρ-value Variance Assumed = 0.92; Variance not assumed = 0.92
[29]	Hough transform, Contrast stretching and K-means clustering algorithm	Less computational complexity	This procedure was not carried out correctly due to the incorrect entry of the pre-processing image.	The response time of this model was less than 2 mins.
[30]	Greyscale conversion algorithm, Sobel technique and SVM algorithm	This method has a simple structure and efficiently detects edges and their orientation	On using the SVM algorithm, this model might underperform on large training data	Overall accuracy = 85%
[31]	FRCNN with the Inception ResNet_v2_Atrous and SSD Inception_v2	This method provides standard and consistent results through the complete performance.	High time complexity	Average precision (AP) ranges from 97.41% to 99.09
[32]	DNN and SALT score	Does not require any strict control images	This model has limited generalizability	Jaccard similarity indices for scalp = 94.1%; and HL area = 96.3%
[33]	CE-PTG-EC and SCS	This model has fewer classification problems	In contrast to the extensive analysis approach, the physician focuses on the worst damaged locations, resulting in little fluctuation in SCS.	-
[34]	SVM and KNN	This technique proved to be effective and resilient in identifying two separate samples of hair images.	Applying small datasets with no clinical data	Accuracy of SVM = 91.4% and KNN = 88.9%,
[35]	Logistic regression, classification trees, random forest, SVM, KNN, XGBoost and neural network	This method is more reliable and effective in identifying salient features in complex datasets.	This method needs large datasets for this performance.	Area Under Curve for logistic regression = 87.9%; classification trees = 79.9%; SVM = 76.3%; KNN = 79.9%; XG-boost = 80.6%; neural network algorithms = 80.6%

[36]	Clips expert system language	Less computational complexity	This method could not diagnose the disease if more than one symptom of different diseases were selected.	-
[37]	EfficientDet, YOLOv4 and DetectoRS	Better convergence rate	Insufficient number of training datasets for an automated HDM	Accuracy for EfficientDet = 64.71% , YOLOv4= 75.73%, and DetectoRS = 66.36%

4. Discussion

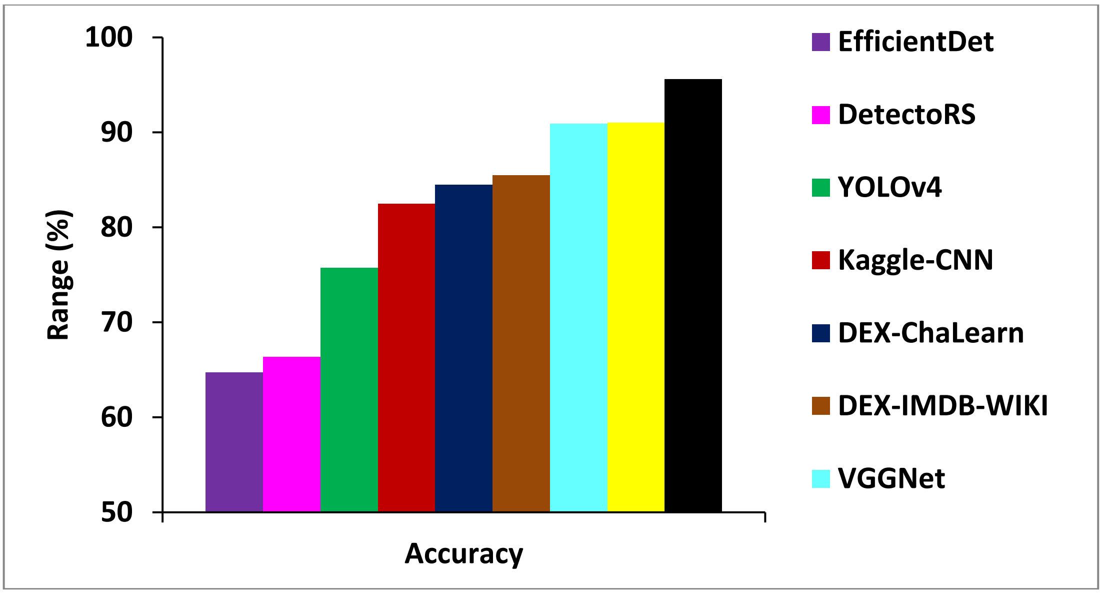

Fig. 3 Comparison of Accuracy

Further, Figure 3 depicts the accuracy of the FRCNN-Inception ResNetV2-Atrous [31] model compared with the other ML and DL models, including VGGNet [21], FFANN [25], Kaggle-CNN [27], DEX-IMDB-WIKI [27], DEX-ChaLearn [27], EfficientDet [37], YOLOv4 [37] and DetectoRS [37]. This analysis summarises that the FRCNN-Inception ResNetV2-Atrous model has more accuracy than all other ML and DL models in detecting and diagnosing AA.

From Table 4, the article [12-37] is studied and concluded with the Figure 3 experimental that the article [31] yields better classification accuracy for AA detection. In the article [31], the DL has been efficiently used to detect AA diseases, and this method provides some major advantages which could provide an efficient result for AA disease detection are:

- It eliminates the considerable expense and duration of learning and practicing for scalp hair therapists.
- It decreases the errors and inconsistencies of various individual translators.
- Each scalp hair observation analysis outcome may be communicated to an accessible cloud-based administration network, which can assist connected companies like scalp hair therapeutic clinics and beauty salons in tracking the development of scalp-hair care, remedies, and client solutions.
- It keeps cloud-based scalp hair data for consumers, allowing scalp hair physiotherapists to follow and evaluate their clients' scalp hair health status on a constant schedule.
- The created cloud-based administration infrastructure easily manages client subscriptions.

5. Conclusion and Future Scope

This survey presents a detailed comparative analysis of AA diseases based on different AI techniques. From this comparative analysis, it is understood that all researchers who have conducted experimental analysis on AA diseases using AI techniques on different datasets for predicting the HL and scalp disorder symptoms find some limitations like less detection value, low performance on large datasets, etc. Therefore, the future extension of this study could resolve all these above-considered issues by deeply focusing on deep learning approaches, including Convolutional Neural Network to detect AA and scalp conditions together.

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