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REVIEW ARTICLE

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How good is artificial intelligence (AI) at solving hairy problems? A review of AI applications in hair restoration and hair disorders

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Abstract

Artificial intelligence (AI) applications in medicine are rapidly evolving. Deep learning diagnostic models that can accurately classify skin lesions have been developed. New AI applications are also starting to emerge in the hair restoration field. The objective was to review the current and future clinical applications of AI in hair restoration and hair disorder diagnosis. Current AI applications in hair restoration include fully automated systems for hair detection and hair growth measurement. New deep learning-based systems have been proposed for scalp diagnosis and automated hair loss measurements, including devices that can be used for self-diagnosis. Hair restoration experts should recognize the potential benefits and limitations of these emerging technologies as they become more readily available to both clinicians and patients.

KEYWORDS

artificial intelligence, deep learning, hair disorder, hair restoration, machine learning

1 | INTRODUCTION

Artificial intelligence (AI) is often perceived as an abstract and futuristic concept. However, most of us use AI technology in our everyday lives from voice recognition applications to Google searching.[1] AI refers to computer algorithms that can perform tasks that would normally require human intelligence. In the field of medicine, advances in AI image classification have been used to diagnose certain skin cancers from clinical photographs potentially with the same accuracy as a highly trained dermatologist.[2] The type of AI used for image classification is called *deep learning*, which uses layered algorithms to form an artificial neural network, which can learn from inputted data to identify and categorize information. In other words, it can be trained on annotated images to accurately categorize or "diagnose" unmarked images. The application of deep learning to dermatology is an enormous advancement since the skills required to make an accurate dermatologic diagnosis often require exposure to thousands of patients over many years. This time investment in skill accruement is also true for hair restoration specialists where extensive experience is needed to make accurate diagnoses and predictions. In this regard, through annotated image training, AI can quickly acquire the accuracy of an experienced physician and lend this experience to budding clinics. AI deep learning applications in the field of hair restoration are just starting to emerge. These new technologies have the potential to fundamentally change our approach to hair loss diagnosis and treatment.

1.1 | Artificial intelligence, machine learning, and deep learning

AI algorithms can accomplish different tasks by using preprogrammed instructions, or by learning from input data (machine learning). The more advanced the machine learning algorithm, the less human specification it requires.[3] There are different types of machine learning (Figure 1), and supervised learning algorithms are commonly used in medicine.[4] In supervised learning, algorithms learn how to perform tasks from examples with known outcomes (training). Then, the algorithm's ability to predict the correct outcome from an unknown example is evaluated (testing), and internal parameters are adjusted until the output is acceptable.[5] Classification or regression machine

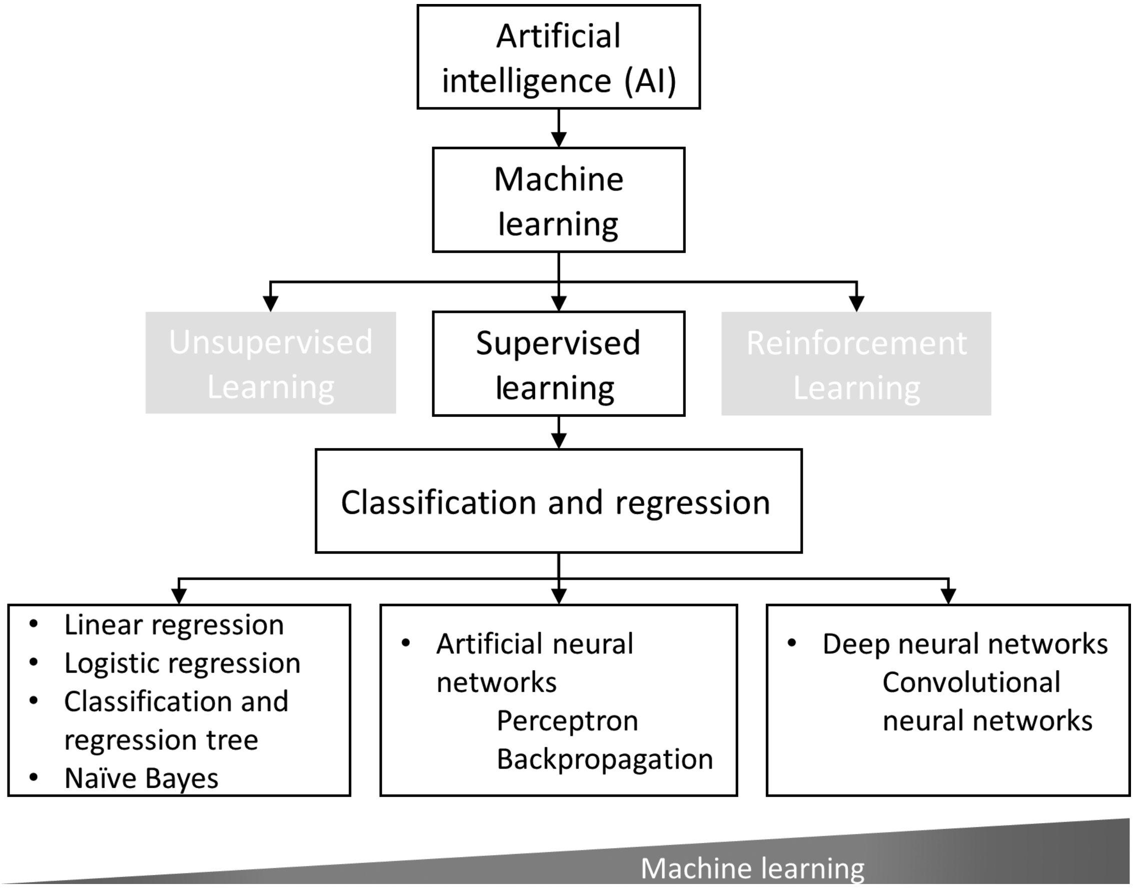

FIGURE 1 Artificial intelligence algorithms in medicine. Machine learning (ML) is an AI subset referring to algorithms that learn to perform tasks from input data. From the different types of ML, supervised learning is commonly used in AI applications for medicine. Supervised ML models are trained to perform tasks using examples with known outcomes. Classification and regression ML algorithms are used to predict discrete (eg, positive or negative) and continuous (eg, cardiovascular risk) outcomes. Algorithms that can make a diagnosis or prognosis with minimal human intervention (deep neural networks) rank high on the ML spectrum

learning algorithms are used in medicine to predict discrete (eg, benign vs malignant) or continuous (eg, life expectancy) outcomes, respectively.[4] The Framingham cardiovascular risk score is an example of a machine learning algorithm that was developed with significant input from clinicians and statisticians. Therefore, it ranks low on the machine learning spectrum. Deep learning models score high on the machine learning spectrum because they can make a diagnosis or prognosis based on input data without human intervention[3] (Figure 1).

Deep learning is a specific form of machine learning referring to algorithms that imitate biological neural networks (NNs). An artificial NN consists of input, hidden, and output layers that receive and process data, and produce a result (output). Each layer contains multiple, interconnected artificial neurons composed of mathematical functions, which receive input(s) and produce an output (Figure 2A).[6] Simple (shallow) NNs only have one hidden (data processing) layer (Figure 2B), whereas deep NNs can have multiple hidden layers and a much greater data processing capacity (Figure 2C).[7] Image analysis NNs typically contain one or several convolutional layers responsible for image processing. Dermatology-specific deep learning approaches have been used successfully to classify skin lesions from dermoscopy images and to predict skin cancer susceptibility.[8] Most dermatology deep learning models are designed for diagnosis of skin lesions. Images annotated by a dermatologist are used to train the NN until it can accurately classify different types of skin lesions. Similar approaches could be developed for hair loss diagnosis (Figure 3A,B).

Here, we review the current AI-assisted methods for hair loss diagnosis and treatment. We also discuss new developments in AI applications for hair loss diagnosis and their implications for treatment and prognosis (see Table 1).

2 | HAIR LOSS DIAGNOSIS

2.1 | AI-assisted hair growth analysis

Successful hair restoration therapy requires methods that can accurately measure hair growth characteristics (hair number, density, diameter, and growth cycle phase) at baseline and after an intervention to determine treatment efficacy. Early AI algorithms for hair detection

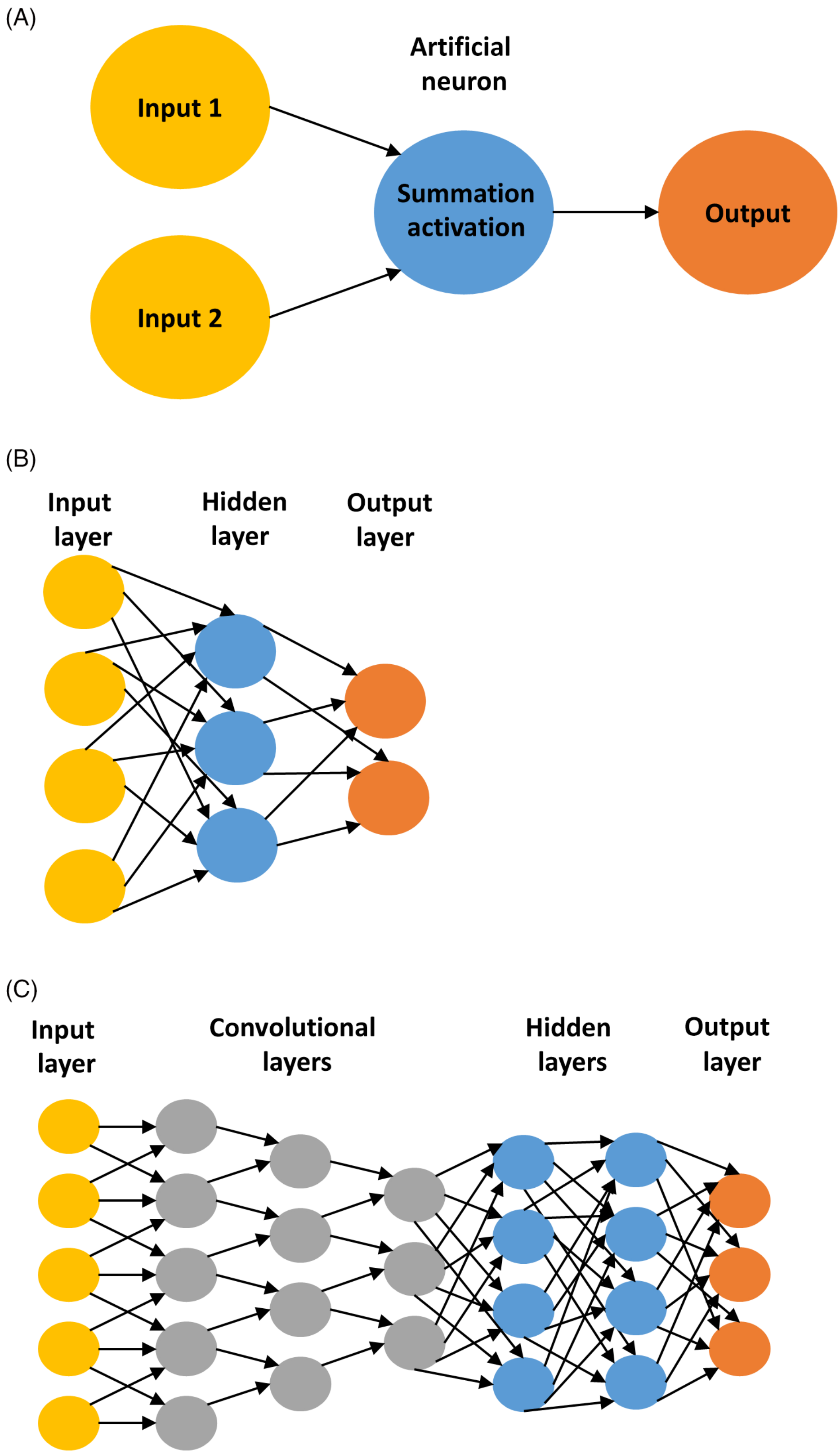

FIGURE 2 Artificial neural networks (NNs). Artificial NNs are nonlinear machine learning algorithms modeled on biological neural networks. A, The basic processing units of NNs are artificial neurons consisting of mathematical functions that receive input(s) and produce an output. B, NNs are made up of multiple, interconnected neurons that are arranged in layers. Data are received by the input layer, then processed in the hidden layer, and the output layer predicts an outcome based on the data. C, Deep NNs have multiple hidden layers, thereby increasing their data processing capacity. Deep NNs used for image classification contain multiple convolutional layers

were not designed for hair analysis, but rather to remove hairs from dermoscopy images because they can obscure skin lesions and interfere with diagnosis. The DullRazor algorithm was developed to detect and remove dark hairs from pigmented skin lesion images.[30] E-shaver is an improved version of the DullRazor algorithm capable of detecting both light and dark hairs.[9] Several other algorithms have been developed to improve hair detection and removal from dermoscopy images, and to reconstruct the missing pixels in the image.[31,32]

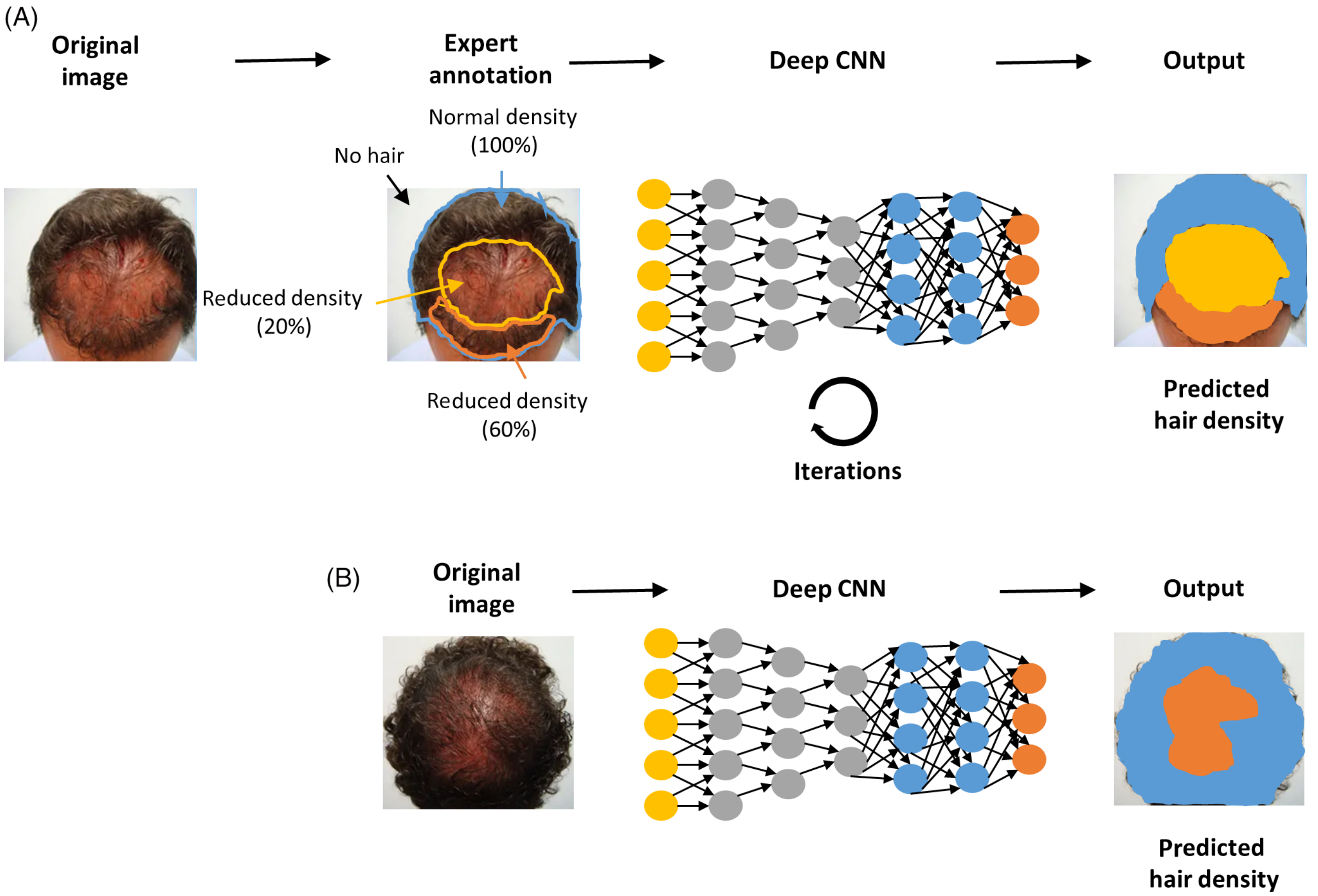

FIGURE 3 Possible deep convolutional neural network (CNN) applications in hair restoration. A, Training. A database of scalp images annotated by hair restoration experts can be used to train the deep CNN to detect scalp regions with reduced hair density. Over multiple iterations, internal parameters in the network are adjusted until the predicted hair density values are acceptable. B, Testing. A new, unlabeled database of scalp images is used to test the ability of the CNN to accurately identify regions with reduced hair density

Hair detection algorithms were later developed for hair analysis. The TrichoScan system incorporates epiluminescence microscopy and fully automated image analysis.[11] It significantly increases the accuracy and reproducibility of hair measurement as compared with manual image annotation.[12] TrichoScan analysis can be used to select patients for hair transplant procedures by ensuring sufficient hair density in the donor area.[13] A limitation of the system is that the hair has to be trimmed short and dyed to ensure accurate detection by the software. Automated hair counting systems can also be used for body hair measurements. A flatbed scanner system was used to acquire images, while correcting for body curves to ensure that the images were in focus. AI algorithms then explored line segments in these images, and assembled them to form hair traces and analyze hair density and diameter. However, hair had to be trimmed to 4 mm to avoid hair crossing, which interfered with image analysis.[14]

Trimming and dying the hair to prevent hair crossing and ensure high contrast between hair and scalp is necessary for accurate automatic detection with these systems, but it is not practical for all applications as it limits the scalp area that can be analyzed. Therefore, fully automated systems have been developed to detect and analyze untrimmed hair. Folliscope (LeadM Corp., Seoul, South Korea) can be used for acquisition and analysis of scalp microscopic images, and measurement of hair density and diameter[15,16] Hairmetrix (Canfield Scientific) is a system that can detect untrimmed hair in dermoscopic images, and analyze hair density, diameter, and the terminal:vellus hair ratio.[17] Both systems use proprietary AI algorithms.

This new technology is still evolving as other AI algorithms able to detect and analyze untrimmed hair are being developed. A modified Hough transformation algorithm was used to design an automated hair counting system able to assess different length hairs growing in different orientations. The algorithm could also correct for image saturation caused by oily spots on the hair, wavy or curly hairs, and crossed hairs.[18] Another algorithm for microscopic scalp image analysis achieved 91% precision in detecting hairs and 95% accuracy in determining hair thickness.[19] Deep learning approaches have also been applied for hair analysis. A convolutional NN (CNN) was developed to detect hair follicles in scalp dermoscopy images with significant differences in skin and hair color,[33] and a deep CNN with 23 layers achieved better accuracy at predicting the location of hair follicles than the benchmark CNN.[20] These new models are still experimental, but they indicate that deep learning applications for hair detection will lead to improvements in current technology.

TABLE 1 Select artificial intelligence algorithms for diagnosis of hair-related conditions

Algorithm	Description	Reference
DullRazor	Detects and removes dark hairs from pigmented skin lesion images for more accurate analysis.	Lee et al (1997)[9]
E-Shaver	Improved DullRazor: faster, removes *light*, *thin* hairs as well.	Kiani et al (2011)[10]
Trichoscan	Detects hair density, hair diameter, hair growth rate, and anagen:telogen ratio (for the latter, measurements must be taken 3 days apart). Combines standard epiluminescence microscopy with automatic digital image analysis. Hair has to be trimmed short and dyed. Hairs smaller than 5 mm cannot be analyzed.	Hoffmann (2003),[11] Gassmueller et al (2009),[12] and Kolasinski (2009)[13]
Body hair counting	Automated hair counting systems for body hair measurements, exploits the fact that hair strands are straight locally. Need to trim the hair.	Vallotton and Thomas (2008)[14]
Folliscope	Measurement of hair density and diameter of untrimmed hair.	Lee et al (2012);[14] Birnbaum et al (2018)[16]
Hairmetrix	Detects untrimmed hair; analyzes hair density, diameter, and terminal:vellus hair ratio. Can calculate anagen:telogen ratio on clipped hair.	HairMetrix brochure[17]
Modified Hough transformation	Automated hair counting system assesses different length hairs growing in different orientations, can correct for image saturation caused by oily spots, wavy or curly hairs, and crossed hairs. Hair must be a different color from the scalp.	Shih (2015)[18]
Microscopic scalp image analysis	Hair counting system that also corrects for oily patches and crossing hairs. Achieved 91% precision in detecting hairs and 95% accuracy in detecting hair thickness.	Kim et al (2017)[19]
Convolutional neural network (CNN)	Based on system that counted hair follicles instead of hair, uses images of neighboring hair to facilitate counting of hair follicles within chosen section (average pooling); 14 layers.	Podlodowski et al (2018)[20]
"Deeper" CNN based on VGG-16 algorithm	Similar to above CNN, with 23 layers instead. Also uses average pooling.	Podlodowski et al (2018)[20]
ScalpEye (Faster R-CNN with Inception ResNet_v2 _Atrous algorithm)	Different deep learning modules, achieved 97%-99% precision in detecting dandruff, folliculitis, hair loss, and oily hair	Chang et al (2020)[21]
CNN for hair tone estimation	Accuracy in estimating hair color, lighter architecture than other similar CNNs (fewer convolutional layers, separable 2D convolutions)	Bokaris et al (2019)[22]
Automated Severity of Alopecia Tool (SALT)	Calculates percentage of hair loss and hair density in alopecia areata patients based on percentage of scalp surface area involved using texture analysis and shape contexts.	Olsen and Canfield (2016);[23] Bernardis, Castelo-Soccio (2018)[24]
Feed forward backpropagation neural network	Early diagnosis of alopecia areata, 91% accuracy.	Kapoor and Mishra (2018)[25]
Computer-aided imaging system	Measures width of central balding area of female pattern hair loss using the Chan and Vese level-set scheme.	Hung et al (2015)[26]

(Continues)

TABLE 1 (Continued)

Algorithm	Description	Reference
"Intelligent hair and scalp analysis system"	Analyzes pictures of the crown for self-diagnosis of hair loss and scalp conditions, corrects for differences in lighting.	Lee and Yang (2018)[27]
Deep learning-based detection of hair loss	Analyzes facial images, self-diagnosis of level of hair loss. The highest accuracy was exhibited by the Deep EXpectation (DEX) on apparent age method using the VGG-16 architecture.	Benhabiles et al (2019)[28]
ARTAS	FDA-approved hair restoration system. Tracks patient movement with multiple cameras using markings on skin tensioner. Computes angle, orientation, density, and location of follicular units (FUs) using imaging algorithm. Chooses FUs based on configurable input by the physician. Scores then dissects FUs, compensating for patient movement.	Berman (2011)[29]

Hair growth rate is an important indicator of hair health. The anagen:telogen ratio, or the proportion of actively growing vs dormant hair follicles, is a parameter that is used in hair disorder diagnosis and to determine treatment efficacy. Currently, all available methods to measure the anagen:telogen ratio involve shaving a scalp area and measuring the growth of new hair shafts over time. Methods to measure anagen:telogen by dying hair shafts at the base and monitoring outgrowth have been proposed,[34] but have not been implemented in clinical practice. New advances in deep learning-based hair imaging may facilitate the implementation of better methods to accurately measure hair growth.

2.2 | Deep learning-based systems for scalp diagnosis

Diagnosis of scalp conditions requires dermoscopic examination by a specialist. Since more hair and scalp treatments are being offered in nonspecialist settings, new AI-based systems using an imaging device and an online deep learning database for image classification have been proposed for diagnosis of scalp conditions.[35-37] The prototype system (ScalpEye) was tested using different deep learning modules and achieved 97%-99% precision in detecting dandruff, folliculitis, hair loss, and oily hair.[21] A similar approach was used for a cosmetic application—hair tone estimation before hair coloring. A prototype device was used to acquire over 11 000 scalp images with hair tones ranging from light blond to black. Several CNNs were tested for accuracy in estimating hair color. The shallowest CNN model had the best performance and accuracy, and could run on a computer chip integrated in the device.[22] These studies indicate that development of portable scalp diagnosis devices incorporating image databases and deep learning-assisted analysis is possible. Although such systems are not available for clinical use yet, it is now possible to envision how in the near future they could aid the diagnosis of rare scalp and hair disorders that may otherwise be misdiagnosed.

2.3 | Hair loss diagnosis

In addition to microscopy methods used to examine the hair and scalp, visual inspection and scoring of the severity and pattern of hair loss are used for diagnosis of hair disorders. Machine and deep learning approaches have recently been used to facilitate alopecia areata diagnosis. The Severity of Alopecia Tool (SALT)[23] captures the percentage of hair loss and hair density in alopecia areata patients. The scoring system is complex and difficult to generalize, which can affect reproducibility among users. However, reproducible scoring is essential for monitoring disease progression and treatment efficacy. To improve scoring reproducibility, an image database of 100 patients was annotated by a hair expert, and an algorithm was developed that could delineate normal and bald scalp areas and identify regions with low hair density.[24] In a different study, a deep NN was developed to determine the SALT score. Over 2000 images of 18 alopecia areata patients annotated by a dermatologist were used to train the network. To test the program, eight dermatologists assessed 400 images manually and with its assistance. The program-assisted approach improved accuracy and interrater reliability.[38] A machine learning method has also been proposed for early diagnosis of alopecia areata. Healthy and affected individuals were classified based on hair and nail attributes. The NN was able to classify healthy individuals and alopecia areata patients with 91% accuracy.[25]

A similar approach was used for diagnosis of female pattern hair loss (FPHL), which is typically done by visual inspection and scoring of the balding area using the Ludwig and Savin scales.[39,40] Crown images of 33 women with FPHL were automatically analyzed by a machine learning algorithm. The values for the balding area width determined by the algorithm were significantly correlated with Savin scale hair loss grades.[26]

AI-based systems have been proposed for self-diagnosis of hair loss. An algorithm was developed to classify crown images obtained with a webcam based on the Hamilton-Norwood scale.[41] The algorithm corrected for different lighting conditions, and classified the degree of hair loss with 51%-95% accuracy depending on the pattern.[27] A different approach was used for detection of male pattern baldness in facial images. Classes 1-3, corresponding to type 1, type 2-4, and type 5-7 of the Hamilton-Norwood scale, were used to classify 675 images. Three different CNNs were tested and achieved an average accuracy of 82%-86% in image classification.[28]

Accurate and reproducible determination of hair loss extent and pattern is critical for diagnosis of hair disorders and for monitoring treatment efficacy. The clinical implementation of deep learning-based approaches for hair loss scoring would increase reproducibility and facilitate treatment follow-up.

3 | HAIR LOSS TREATMENT

AI-assisted technology is also being used for hair loss treatment. Currently, the only FDA-approved robotic hair restoration system is the ARTAS, which allows for image-guided follicular unit (FU) excision.[42] The system uses patented AI technology to detect the location, angle, and direction of follicular units.[43-46] Then, it guides a robotic arm to excise the FUs in a random pattern to minimize scarring.[29] Hair has to be trimmed to ensure accurate FU detection and excision. In the newest version of the system, a digital recipient site plan can be programmed by the surgeon to allow for automated FU transplantation. With advances in deep learning technology, it may be possible to develop systems which can predict how the patient's hair loss pattern will develop over time, to allow for accurate delineation of both donor and recipient areas.

4 | LIMITATIONS

New deep learning models can be equally good or better than clinicians at performing a well-defined task, such as diagnosing specific skin diseases using unlabeled images, raising concerns about the increased reliance on these models in clinical decision making.[47] However, the prediction accuracy of deep learning models depends on the quality of the training data sets, which require careful annotation by experts. Inaccurate training data reflect on the quality of the results. A statement issued by the American Academy of Dermatology on the concept of augmented intelligence, or the assistive role of AI, emphasized that AI applications should be designed to enhance, but not replace, the physician-patient relationship.[48] Physicians should have an active role in developing these tools to facilitate their successful implementation in clinical practice.

5 | CONCLUSIONS

Deep learning applications in hair restoration are rapidly evolving. Improved methods for measuring hair growth characteristics will facilitate the diagnosis and treatment of hair disorders. Deep learning databases for classification of scalp dermoscopy images will require a significant and collaborative effort from hair specialists for image annotation, but could become valuable diagnostic tools. New prognostic tools for hair loss modeling could help guide hair restoration decisions. These new technologies will be available to both clinicians and patients, and hair restoration experts should understand their potential benefits and limitations.

CONFLICT OF INTERESTS

Mediprobe Research Inc. is a not-for-profit, non-commercial research group, thus Aditya K. Gupta, Iordanka A. Ivanova, and Helen J. Renaud have no conflict of interest to declare.

AUTHOR CONTRIBUTIONS

Aditya K. Gupta: Conceptualized the project. Aditya K. Gupta, Iordanka A. Ivanova, and Helen J. Renaud: Substantial contributions to the conception/design of the work; Iordanka A. Ivanova: Performed the literature search; Aditya K. Gupta, Iordanka A. Ivanova, and Helen J. Renaud: Identified and reviewed the relevant studies; Iordanka A. Ivanova: Drafted the work; Aditya K. Gupta, Iordanka A. Ivanova, and Helen J. Renaud: Revised the draft. All authors have approved the submitted version.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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