International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(23s) 2026 pp. 1016-1029
https://doi.org/10.70917/ijcisim-2026-5680
Article

An Intelligent Deep Learning Framework for Automated Alopecia Areata Detection and Severity Evaluation

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Abstract: Objective: The goal of this research is to use scalp and hair images to create an efficient deep learning framework for the automated detection and severity categorization of Alopecia Areata (AA). Methods: Using scalp and hair images collected from the Derm-Net and Figaro1K databases, the proposed ADAR-Net framework is developed to detect and assess Alopecia Areata. Important local and global characteristics are first extracted from the input images by two distinct FRCNN-based encoder networks. The model combines Cross-Residual Learning (CRL) and Multi-Task Learning (MTL) strategies to improve feature learning and enhance information transfer between related tasks. The relationships between the collected characteristics are then captured by combining them and passing them via an LSTM layer. However, the model is able to focus on the most important areas of the images while minimizing the impact of irrelevant data thanks to Channel Attention and Spatial Attention methods. The images are then classified into four categories: Healthy Alopecia Areata, Mild Alopecia Areata, Moderate Alopecia Areata, and Severe Alopecia Areata after the improved features are put into a fully connected layer and a SoftMax classifier. Conclusion: The test findings demonstrate that, in comparison to all previous conventional systems, the proposed Attention-Driven Alopecia detection Network (ADAR-Net), which is designed to enhance the automated detection and classification of Alopecia Areata using hair and scalp image databases, achieves an accuracy of 95.1%. Novelty: The combination of the CRL, MTL, LSTM, and attention processes in a single model for Alopecia Areata identification is what makes this work innovative. By using attention-guided learning, the suggested architecture concurrently learns complementing scalp and hair characteristics and improves their representation.
Keywords: Dermatological Classification, Scalp Image Analysis, Deep Learning, Multi-Task Learning, Cross-Residual Learning, Alopecia Areata

1. INTRODUCTION:

With the growing incidence of hair and scalp diseases, scalp-related disorders are an important area of research in dermatology. Several diagnostic methods were proposed to identify abnormalities located in the scalp, but it is still difficult to accurately recognize each of the different types of scalp conditions due to the similarity among the visual symptoms and the complexity of the scalp textures [1]. In recent years, mathematical techniques of artificial intelligence and deep learning have advanced greatly, and such advances have had great impact on automated medical image analysis systems, particularly in dermatological applications such as examination of the scalp and hair. [2] Different smart scalp analysis systems have been created to automatically analyze the micro image of the scalp and support the diagnosis of the diseases. Advanced feature extraction methods enable deep learning-based systems to detect common skin conditions on the scalp, including psoriasis, dandruff, hair thinning, cellulitis, and baldness. [2] Typically, these systems comprise image capturing modules, diagnostic engines on the web and automatic classification modules for effective scalp condition monitoring. Recently, convolutional neural networks and residual learning models have had successful applications to determine complicated scalp abnormalities from image datasets.

Alopecia Areata (AA), which is manifested by sudden non-scarring hair loss in discrete areas of the scalp, is one of the most common scalp disorders affecting about 2% of the population throughout life [3,4]. Because the process of disease progression is best, the treatment can be more effective if the diagnosis is made early. Trichoscopy and biopsy-based studies (which require some experience and take time and might not be applicable for wide screening applications) are conventional diagnostic methods used in AA [5]. This means that computer-assisted methods are necessary to enhance the efficiency and accuracy of diagnosis.

In recent years, the use of deep learning algorithms for scalp and dermoscopic image analysis for the diagnosis of hair loss disorders has proven to be effective [6–8]. However, most of the current models are difficult to train both local scalp patterns and global feature representations simultaneously. Moreover, most traditional machine learning and deep learning methods show poor generalization to various and complex scalp image datasets.

In this work, a multi-task deep learning framework is proposed to address the mentioned drawbacks: automatic recognition of Alopecia Areata and analysis of the condition of the scalp using an attention mechanism. The proposed system consists of multi-task learning and cross-residual learning techniques to enhance the representation of discriminative scalp & hair features. To represent the local and global characteristics of the image at various scales, hybrid deep architecture is used, which includes Faster Residual Convolutional Neural Networks (FRCNN) and Long Short-Term Memory (LSTM) networks. Learning tasks can be related, so that cross-residual connections enable effective knowledge sharing among learning tasks and better generalization across the network. In addition, the framework is enhanced by the addition of attention mechanism, which assigns higher weights to diagnostically relevant scalp regions while lower weights are assigned to the irrelevant background information.

The extracted feature representations are then fed into fully connected layers and SoftMax classifier to correctly classify various AA conditions. The contributions of this work are as follows: (i) Cross-residual learning (CR) method for efficiently transferring knowledge between different related tasks; (ii) multi-task deep learning architecture with FRCNN, LSTM and attention mechanism for extracting comprehensive features; (iii) Unified framework to improve the classification performance of Alopecia Areata and analyze the condition of the scalp. The experimental results demonstrate the performance of the proposed framework in classification process when evaluated in comparison to the conventional machine learning and deep learning-based system which reveals the significance of cross-task feature integration in the intelligent dermatological diagnosis system.

2. RECENT WORK:

In this regard, a number of research studies have studied the diagnosis of scalp diseases using artificial intelligence and deep learning technology and detection of hair loss. Various computational frameworks have been proposed to boost the identification and classification of Alopecia Areata (AA) and other scalp-related abnormalities. A Deep Neural Network (DNN)[9] was developed to estimate the Severity of Alopecia Tool (SALT) score and to detect affected areas on the scalp of patients with AA. In this method, the texture-based analysis was performed on the scalp images processed before to detect the region of the lesions. The framework is successfully effective in diagnostic performance, but the data obtained in this research are still obtained from a single medical institution, making the diagnostic model difficult to generalize. Furthermore, the training process was time consuming and was affected by artefacts in the images due to errors in the illumination and exposure conditions. A pre-trained image processing-based scalp disease classification framework [10] was also developed for automatizing the scalp condition recognition. The first step in this process was to obtain and preprocess scalp images, in order to enhance image quality. The Region of Interest (ROI) was extracted after preprocessing by multiple visual characteristics including texture, shape and color information. The extracted pre-trained features were then used for disease categorization using Support Vector Machine (SVM) classifier. The framework, however, took a long time in processing and was examined only in a relatively small data set. A lightweight CNN model, Hair Diagnosis Mobile Net (HDM-Net) [11] was proposed to identify the severity of hair damage. The extracted features were further classified using an SVM based classifier and the architecture HDM-Net was used for efficient feature extraction and feature selection. The framework limited the number of trainable parameters and computation, but the classification precision was not high enough to be used in practice. The trichoscopic properties of Female Pattern Hair Loss (FPHL) among Chinese Han patients were analyzed in another study [12]. In this concept, photographs of the hair were taken from various regions of the scalp and analyzed to assess various trichoscopy parameters including hair density, hair shaft thickness, vellus hair ratio, and follicular unit percentage. The variations between male and female FPHL patients were also investigated. However, the study made use of small samples of data, and the results were not applicable to wider, healthier populations. A machine learning based classification method [13] has been developed for classification of healthy hair conditions from Alopecia Areata. The initial processing and segmentation of scalp and hair images was performed into various regions. Each segment subsequently underwent a number of visual features such as texture, shape and color features. The last two classifiers, SVM and KNN, were applied for the classification of healthy and AA conditions. Although the performance is moderate, the classification accuracy declined in the case of the large-scale dataset. In addition, a deep learning framework [14] was suggested for automatic trichoscopy scan analysis and quantitative classification of androgenetic alopecia in males. This approach involved processing trichoscopic images of the scalp with a CNN-based deep learning architecture to extract the detailed patterns of the scalp. Several ordinal logistic regression models were then used to predict the primary and detailed alopecia classifications. The sample size for training, however, was small and most participants were from a particular geographical population, which decreased the diversity and robustness of models. Their effectiveness of scalp density analysis using deep learning techniques also was investigated [15]. RGB scalp images obtained from male alopecia patients were used to extract the information on the position of the follicles and to classify the hair follicles into groups based on the number of hairs visible in the images. Advanced object detection models were used for identification and classification of follicles, which are Efficient, YOLOv4 and Detectors. However, the efficiency of the above models for classification was significantly reduced owing to similarity in visual features of some of the groups of follicles, particularly Group-3 sample. Furthermore, the problems of class imbalance negatively influenced the overall prediction performance. Later, an intelligent system for scalp diagnosis and classification was introduced using an automated approach that utilizes the Efficient Net architecture, called AI-Scalp Grader [16]. The framework showed good results, but the accuracy achieved was not satisfactory, from 87.3% to 91.3%, which means there is a need to further improve the diagnostic ability. In a similar fashion, a method with 2D CNN was suggested for recognizing multiple scalp diseases and hair loss disorders on a dataset of scalp images gathered from the internet [17,18]. But the framework was not as effective and generalizable due to the lack of a common dataset and the lack of diversity in the images. The analysis of the previous studies shows that there are still a number of challenges such as limited size of datasets, inadequate representation of features, decreased generalization and decreased classification accuracy in the existing machine learning and deep learning techniques.[19,20] Hence, there is a heavy need of the development of an intelligent framework with advanced capabilities for the effective learning of local and global scalp features for the overall enhancement of the efficiency and reliability of Alopecia Areata diagnosis.

3. Methodology:

A brief explanation of the proposed Attention-Driven Deep Learning Framework for Alopecia Areata Recognition is given in this section. The pipeline of the presented study is presented in a schematic way in Figure 1. Healthy and AA hair and scalp photos for the first are acquired from websites that are easily accessible. These images are then used to train the MT Deep model in accordance with the MTL (Multi-Task Learning) and CRL (Cross-Residual Learning). Furthermore, the learned model is used for the classification of test samples to healthy or different AA states.

Figure 1 shows the overall process of the proposed Attention-Based Multi-Task Deep Learning framework for the classification of Alopecia Areata.

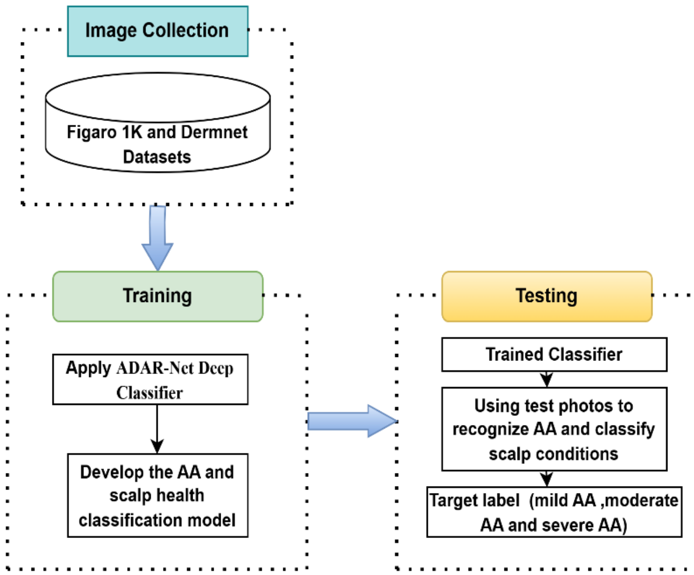

Fig 1. An overview presented Study for AA Classification

3.1 Dataset Description

The two publicly available datasets used to develop and evaluate the proposed model for Alopecia Areata (AA) detection and classification are scalp and hair images. The datasets contain images of both healthy and different stages of Alopecia Areata, which helps the model to distinguish between various classes and learn effectively.

Figaro1K Dataset

The Figaro1K dataset consists of ~1050 hair images of various hair types and textures including straight, wavy and curly hair. A total of 350 images of healthy and normal hair condition were selected for this study. The healthy class consisted of these images to help the model distinguish between healthy and cases of Alopecia Areata.

Derm-Net Dataset

The Derm-Net data set contains images of different skin and scalp diseases, such as Alopecia Areata. This data set was used to collect 1,050 images of Alopecia Areata and classify them in three categories: mild, moderate and severe. There are 350 images in each category and samples are equally distributed across all stages of the disease.

Images from both obtained datasets were digitally merged and a total scalp image dataset was obtained. Before model training, all images were preprocessed to maintain consistent image size and quality. The trained and tested dataset was then used to train and evaluate the proposed ADAR-Net framework. Images of healthy scalp and Alopecia Areata images were shown as representative examples as seen in Figure 2.

3.2 Cross-Residual Learning for Multi-Task Feature Extraction

Advanced extension to the Residual Learning, namely Cross-Residual Learning (CRL) which enhances the feature extraction by enabling the information to be shared across different related tasks. The input features are passed through a shortcut and added to the transformed features learned by the network in a conventional residual network. This process is useful in maintaining important information and use in training deep neural networks effectively.

The output of a basic residual block is given by:

$$y = F(x, W_i) + W_s x \quad \textbf{(1)}$$

In Equation **(1)**x is the feature map that is given as input, F (x, Wi) is the residual feature map learned by the network, and Ws is the shortcut projection used to align the feature maps when needed. Cross-Residual Learning is a method to further enrich learning by providing extra linkages between the related task branches. Each task can use helpful features that were learned from other jointly related tasks as well as task-specific residual information. This cooperative learning approach allows for the network to learn more discriminative and powerful feature representations.

The output of a cross-residual block is:

$$y(t) = F\big(x, W_i(t)\big) + \sum_{j} W(j)x \quad \textbf{(2)}$$

In Equation **(2)** y(t) is the output of the target task t, N is the total number of tasks related to task t, W(j)x is the information provided by the other branches of the task. Such cross-task relationships promote representation sharing and enable the model to learn both task-specific and shared representations at the same time. The proposed work is based on CRL that would be added to the multi-task learning architecture, which would enhance the analysis of scalp and hair images for Alopecia Areata detection. The network learns richer local and global features through the exchange of complementary information between similar tasks, limits the overtraining problem, produces better classification performance and generalization ability.

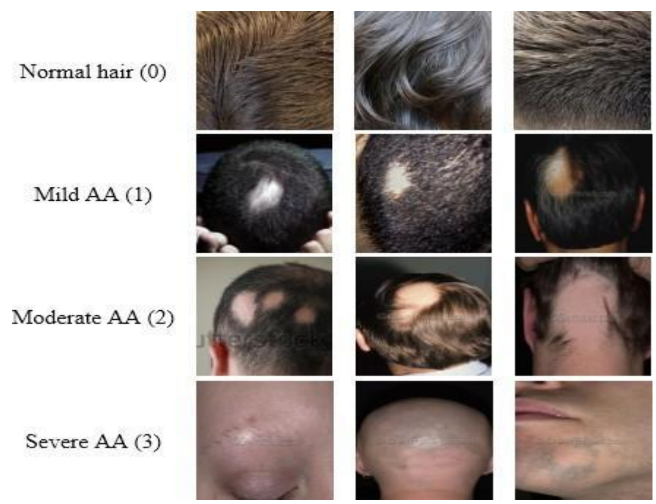

Fig 2.Scalp hair and Alopecia Areata image samples

3.2.1 Early Normalization Strategy

By enhancing model robustness and reducing a possibility of overfitting, regularization and normalization techniques are essential to deep learning optimization. Apart from reducing the prediction error, the purpose of training is to ensure the robustness and generalizability of the feature representations learnt under different types of data. Conventional deep learning models often implement regularization to minimize the number of changes made to the parameters of the network and to smooth the translations of the features**[22]**

In the proposed architecture, the Cross-Residual Learning (CRL) method is used to exchange information among related learning tasks as internal normalization approach. In training, the network enables the representations of features to influence and regulate each other instead of doing each task independently. This collaborative learning approach ensures uniformity across task-specific feature spaces, and avoids the use of extreme specialization towards a specific task. The suggested cross-residual method normalizes directly in the intermediate layers of the network, which is different from the typical normalizing methods that are applied at the end of the loss computation process. The network constantly improves its learnt representations by adding complementary knowledge from related tasks as feature information moves across the cross-residual pathways. As a result, during the training process, feature distributions develop more reliable and informatively.

Another advantage of this approach is to minimize training variability. By having multiple tasks concurrently participating in feature refinement, noise and small changes within certain task branches are less likely to affect the learning process, and thus the model's convergence behavior and its ability to generate reliable feature representations.

Consequently, the cross-residual layer can be regarded as an in-network normalizing process which benefits knowledge sharing, promotes feature consistency, and boosts the generalization capability of the multi-task learning framework. The proposed architecture is more stable and effective in providing training for Alopecia Areata identification by introducing normalization at the stage of feature learning along with output stage.

3.2.2 Connection to Multitask Learning & Residual Networks

Residual networks can be thought of as a reduced version of bridge networks, a network in which the information passes through the network with a shortcut without the need to explicitly use change and carry gates. The output of a bridge layer in a bridge network is defined as:

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \qquad y = H\left(x, W_H\right)T\left(x, W_T\right) + x \bullet C\left(x, W_C\right) \quad \textbf{(3)}$$

The feature mapping is changed in the transformed way by H (x, WH); the change and carry gates are T (x, WT) and C (x, WC), respectively. The number of transformed and original information propagated through the network is controlled by these gates. If both gates are active, the bridge layer is similar to a conventional residual layer.

On this idea, Cross-Residual Learning (CRL) is proposed to include multiple shortcut pathways contributing information in parallel. CRL enables feature representations from related tasks to interact and share knowledge, rather than the use of a single residual connection. These interactions help to develop a more robust representational capacity of the network and the capacity for collaborative learning across task branches.

The same correlation exists between residual networks and Long Short-Term Memory (LSTM) architectures as well. The information flow in an LSTM network is directed by the use of gating mechanisms and memory cells. One input gate, one forgets gate and one cell state update can be expressed as:

$$x_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \quad \textbf{(4)}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \quad \textbf{(5)}$$

$$C_t = f_t\, C_{t-1} + i_t \tanh\left(W_x^C x_t + W_h^C h_{t-1} + b_C\right) \quad \textbf{(6)}$$

Where t: time step, it: input gate, ft: forget gate, Ct: memory cell state, ht: hidden state.

All of these components play a role in regulating the retention, updating and transfer of information during learning. When the recurrent connections are switched off and all the gating mechanisms are assumed to be fully active, the LSTM architecture can be interpreted as a feed-forward residual network. In such situations, information is passed mostly by short-cut ways of information passing, like residual learning. Applying this logic, one can consider Cross-Residual Learning to be a feed-forward network where information from various task branches flows from one module to the other through shared residual units. The cross-residual weights are similar to the memory-control mechanism in that they control what tasks are influenced by the learning of the other. Therefore, the knowledge learned in one task may help the learning process in other related tasks and improve the feature representation and classification performance.

The proposed cross-residual framework is a novel combination of transformed representations and multiple information streams for a particular task, compared to traditional residual networks, which fuse transformed features with a single shortcut connection. This sharing of features allows the network to gather more contextual information and to transfer knowledge between tasks that are related. This enables the proposed framework to attain better generalization property, better feature learning and better performance in Alopecia Areata recognition and disease level classification.

3.3 Multi-Task Cross-Residual Learning-Based AA Recognition Model

This section introduces a multi-task cross-residual learning-based AA recognition model. The proposed Attention-Driven Deep Learning Framework for Alopecia Areata Recognition. Areata recognition which integrates Multi-Task Learning and Cross-Residual Learning. The main purpose of this design is to learn local features of the scalp and global features of the hair simultaneously and to share information efficiently between learning tasks. The architecture is comprised of several feature extraction branches, linked by cross-residual pathways. These connections allow representations related to a given task to interact and enhance the discriminative ability of deeper layers in the network. Consequently, the framework achieves superior feature learning without too large feature spaces as input. In order to further boost the classification performance, an attention-guided mechanism is added on to the network. This module allows the framework to pay attention to informative scalp areas and ignore the background patterns.

3.3.1 **Attention Based Feature Enhancement**

An attention mechanism is introduced to the MT Deep architecture before the SoftMax classification layer in order to improve the proposed framework's feature learning capacity. By reducing the impact of irrelevant background patterns, the attention module enhances the network's ability to focus on informative scalp areas. This is accomplished by identifying features linked to the condition and improving the characteristic maps created throughout the learning process.

Channel Attention and Spatial Attention are the two supporting components of the attention module. The purpose of channel attention is to evaluate each feature channel's value and give channels with discriminative information more weight. This is accomplished by performing L2-normalization across all spatial locations inside each feature channel, which reduces duplicated information and highlights the most relevant channel-wise responses.

The following is an expression for the channel attention operation:

$$A_1(x_{i,c}) = \frac{x_{i,c}}{\|x_{i,c}\|_2} \quad \textbf{(7)}$$

where x_i, c is the feature value at the c-th channel's i-th spatial point.

Spatial attention, on the other hand, concentrates on locating significant areas within the feature map. By analyzing the spatial correlations between pixels, this system produces attention scores that show how important certain visual regions are. To create spatial attention weights, feature values are first standardized across all channels and then processed using a sigmoid activation function.

The definition of the spatial attention function is:

$$A_2(x_{i,c}) = \frac{1}{1 + \exp\left(-\frac{x_{i,c} - \mu_c}{\sigma_c}\right)} \quad \textbf{(8)}$$

where x_i,c represents the feature vector at the i-th spatial position, μc is the mean value of the feature map corresponding to the c-th channel, and σc is the standard deviation.

The network reduces noise and irrelevant visual input while maintaining significant scalp features due to the combined impact of channel and spatial attention. Feature representations thus become more discriminative and appropriate for accurate Alopecia Areata classification.

3.3.2 Proposed Architecture of the Attention-Driven Deep Learning Framework for Alopecia Areata Recognition

Figure 3 shows the overall architecture of the proposed Attention-Driven Deep Learning Framework for Alopecia Areata Recognition (ADAR-Net). It starts by obtaining images of hair and scalp from the Figaro1K and Derm-Net datasets. The images are first preprocessed by resizing the images, normalizing them and augmenting the data with techniques to increase the diversity of the training data and improve the image quality.

The preprocessed images are then fed into two different feature extraction networks, Hair Encoder (FRCNN) and Scalp Encoder (FRCNN). The extracted important features from the images of hair and scalp by these encoders.

Then the extracted features are passed on to the Cross-Residual Learning (CRL) module, which provides the possibility of information exchange between the two learning streams. The Multi-Task Feature Fusion (MTL) module then merges the learnt features in a single feature representation.

Features are then fused and passed through an LSTM network to learn of the context and enhance feature learning. To focus on the most relevant disease-related regions, Channel Attention and Spatial Attention mechanisms are applied. These attention modules increase desirable attributes and diminish the effects of less desirable information.

Lastly, a Fully Connected Layer is used to refine the features and a SoftMax Classifier is employed for the classification. The proposed system categorizes input images into four categories, namely Healthy, Mild AA, Moderate AA, and Severe AA, which will help for the recognition and severity of Alopecia areata.

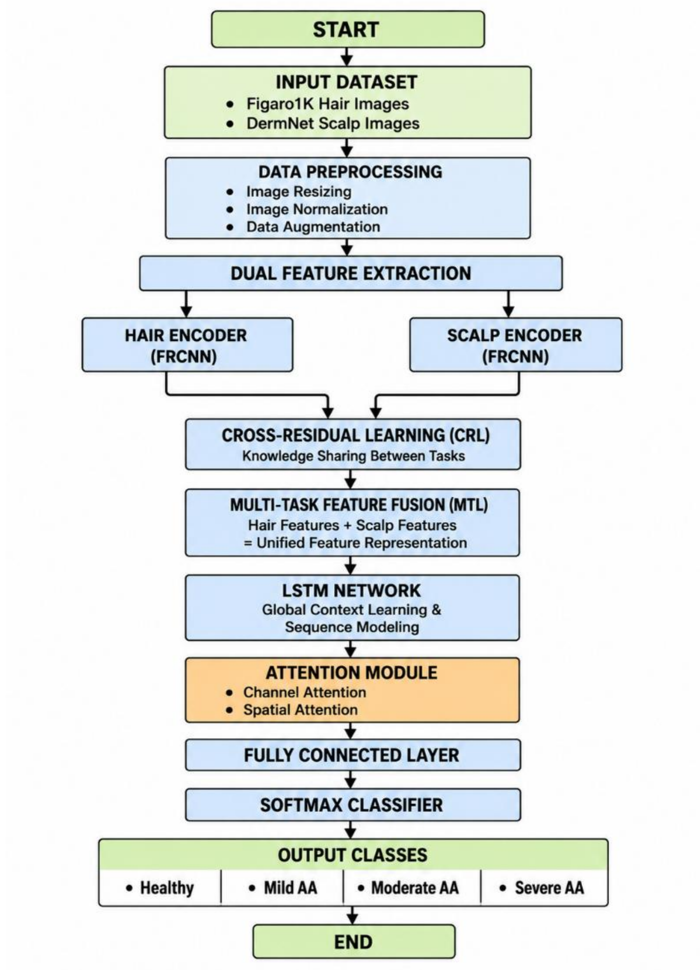

Fig. 3. Overall framework of the proposed ADAR-Net, incorporating dual FRCNN encoders, Cross-Residual Learning (CRL), Multi-Task Learning (MTL)-based feature fusion, LSTM-driven contextual representation, attention-based feature refinement, and SoftMax classification for Alopecia Areata recognition.

4. Results and Discussion

MATLAB R2017b was used to assess the efficacy of the suggested "An Attention-Driven Deep Learning Framework for Alopecia Areata Recognition". The Figaro1k and Derm-Net datasets, which are detailed in Section 3.1, were used for experimental analysis. 1,050 Alopecia Areata (AA) images from the Derm-Net repository and 350 normal hair images from the Figaro1k collection made up the 1,400 scalp and hair images used in the experiment.

The dataset was divided into training set and test set to develop and test the classification model. The model was trained using about 80% of the pictures (1,120 samples), with the remaining 20% (280 samples) were reserved for performance assessment. 840 AA images, which represented mild, moderate, and severe illness categories, and 280 normal scalp images made up the training dataset. The testing set consisted of 70 images of each class across the three classes of severity (210 AA, 70 normal).

The Stochastic Gradient Descent (SGD) technique was used to optimize the proposed network. The batch size used for training was 25, and weight decay and momentum coefficient were 0.0001 and 0.9, respectively. Furthermore, it was decided that a starting learning rate of 0.001 should be used, to ensure good convergence and parameter tuning.

The performance of the proposed framework was tested and compared with some of the existing machine learning and deep learning algorithms, which are mentioned in the literature, such as Scalp Eye [2], Deep Neural Network (DNN) [9],Support Vector Machine (SVM) [10],K-Nearest Neighbor (KNN) [13], YOLOv4 [15] and AI-Scalp Grader [16]. The comparative evaluation was carried out on the basis of some popular classification measures which include accuracy, precision, recall, and F-measure.

4.1 Performance Evaluation Metrics

The following statistical measures were used to evaluate the developed framework's classification ability:[21]

Accuracy

The percentage of correctly categorized samples out of all the samples that were analyzed is known as accuracy. It offers a general assessment of the categorization system's efficacy.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(9)}$$

where:

- TP (True Positive): the number of healthy samples that were accurately classified as healthy.
- TN (True Negative): the number of Alopecia Areata samples that were accurately classified as AA.
- FP (False Positive): the number of AA samples that were incorrectly categorized as healthy.
- FN (False Negative): the number of healthy samples that were incorrectly categorized as AA.

Precision: Precision measures the percentage of correctly predicted positive samples among all positive samples. It shows how consistent the model's helpful predictions are.

$$\text{Precision} = \frac{TP}{TP + FP} \quad \textbf{(10)}$$

Recall: Recallsometimes referred to as sensitivity, measures how well the model can recognize real positive samples. A higher recall value indicates better disease detection capability.

$$\text{Recall} = \frac{TP}{TP + FN} \quad \textbf{(11)}$$

F-Measure: By combining Precision and Recall into a single statistic, the F-Measure offers a fair evaluation of model performance. When there is an imbalance in class distributions, it is very helpful.

$$\text{F-Measure} = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \quad \textbf{(12)}$$

The performance of the suggested An Attention-Driven Deep Learning Framework for Alopecia Areata Recognition was thoroughly examined using these evaluation metrices, and its effectiveness was compared with other approaches for classifying scalp diseases.

Table 1 presents the confusion matrix and indicates the results of each class (normal, mild AA, moderate AA, and severe AA).

Table 1. Confusion Matrix of the Proposed ADAR-Net (Testing Phase)

Actual Class \ Predicted Class	Normal (1)	Mild AA (2)	Moderate AA (3)	Severe AA (4)
Normal (70 Images)	67	1	2	0
Mild AA (70 Images)	1	66	1	2
Moderate AA (70 Images)	0	2	67	1
Severe AA (70 Images)	2	1	0	67

Diagonal values (67, 66, 67, and 67) denote correct classifications, while off-diagonal values indicate misclassifications. The results indicate that the proposed method An Attention-Driven Deep Learning Framework for Alopecia Areata Recognition has good classification performance and has learned the features well, most of the images of the three types of Normal, Mild AA, Moderate AA and Severe AA are classified correctly.

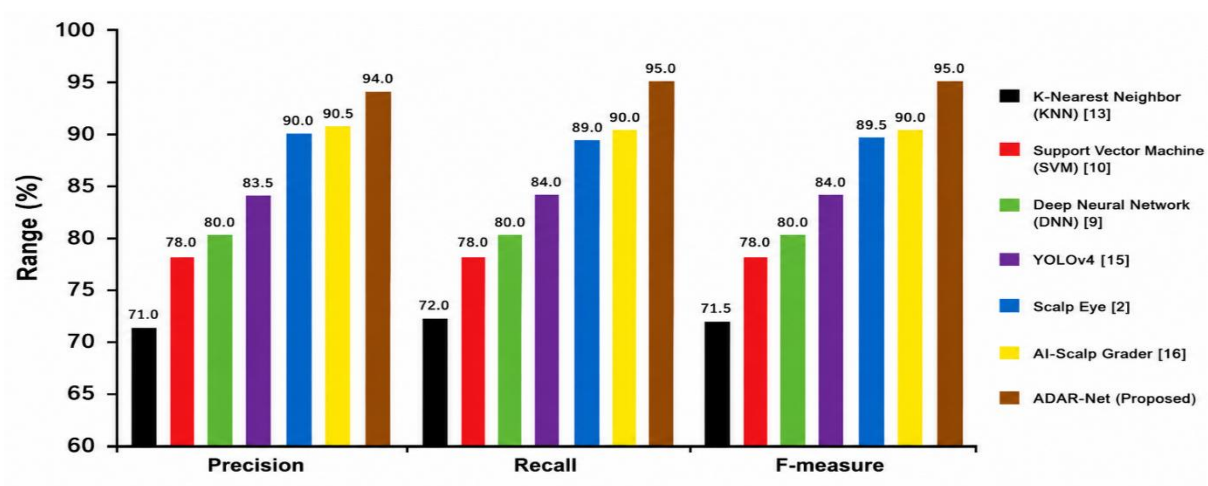

Fig 5. Compared the precision, recall and f-measure of various AA classification models.

Figure 5 Presents the comparison of various Alopecia Areata (AA) classification models using Precision, Recall and F-measure. The results indicate that the proposed method (ADAR-Net) is superior to all compared methods. In terms of Precision, the proposed model achieves approximately **94.0%**, whereas KNN, SVM, DNN, YOLOv4, Scalp Eye, and AI-Scalp Grader achieve about **71.0%, 78.0%, 80.0%, 83.5%, 90.0%, and 90.5%,** respectively. Similarly, the Recall value of the proposed framework reaches approximately **95.0%,** which is higher than KNN (**72.0%),** SVM (**78.0%**), DNN (**80.0%),** YOLOv4 (**84.0%),** Scalp Eye (89.0%), and AI-Scalp Grader (90.0%). For F-measure, the proposed model attains nearly 95.0%, while KNN, SVM, DNN, YOLOv4, Scalp Eye, and AI-Scalp Grader obtain around 71.5%, 78.0%, 80.0%, 84.0%, 89.5%, and 90.0%, respectively. The results show that the proposed ADAR-

Net is more accurate and reliable for the classification of Alopecia Areata. The improved performance is mainly due to the effective combination of Cross-Residual Learning (CRL), Multi-Task Learning (MTL), LSTM-based feature modeling, and attention mechanisms, which enhance feature representation and disease recognition capability.

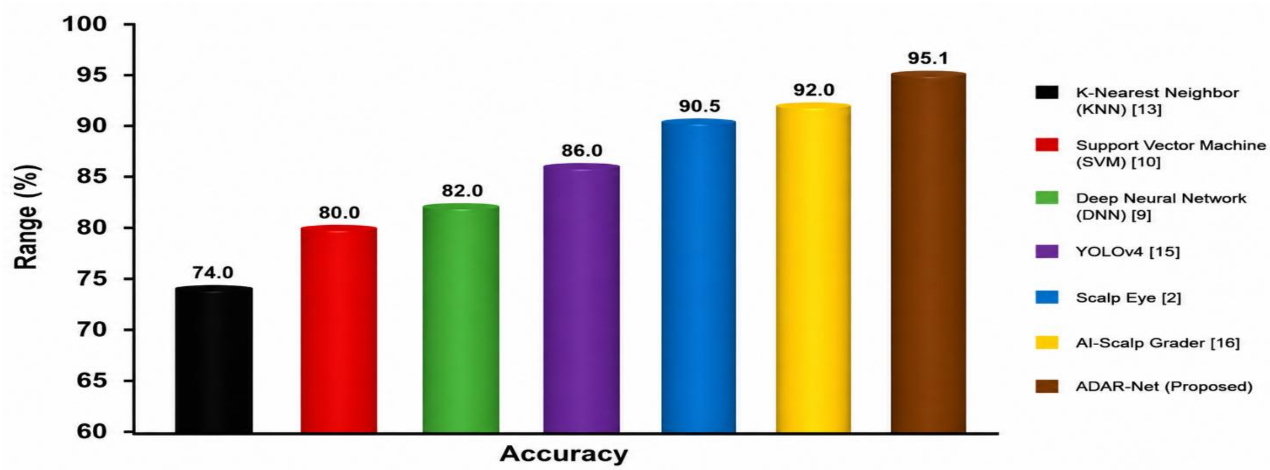

Fig 6. A comparison of the accuracy of various AA classification models.

Figure 6 Presents the classification accuracy of various Alopecia Areata (AA) recognition models. The results demonstrate that the proposed ADAR-Net method achieves the best accuracy compared to the other methods compared. The proposed framework achieves an accuracy of around **95.1%,** whereas the KNN, SVM, DNN, YOLOv4, Scalp Eye and AI-Scalp Grader achieve around 74.0%, 80.0%, 82.0%, 86.0%, 90.5%, and 92.0%, respectively. The proposed model has better accuracy, which shows that the model can classify more accurately different types of Alopecia Areata than the existing models. The main contributions to this improvement are primarily due to the introduction of Cross-Residual Learning (CRL), Multi-Task Learning (MTL), feature modeling using LSTM, and the attention mechanisms. These components facilitate the framework to learn meaningful information from both scalp and hair images, leading to more discriminative feature representations and better classification results. The results validate the suggested ADAR-Net as a stable and solid method for Alopecia Areata identification and severity classification.

5. Conclusion

In this study, the authors introduced an Attention-Driven Deep Learning Framework for Alopecia Areata Recognition (ADAR-Net) for automatic detection and severity classification of Alopecia Areata. The proposed framework combines the feature extraction technique based on FRCNN, Cross-Residual Learning (CRL), Multi-Task Learning (MTL), LSTM-based contextual modeling, and attention mechanism, which can effectively extract the discriminative information from scalp and hair images. The framework is able to enhance recognition of different conditions of Alopecia Areata by integrating local and global feature representations.

The results of the experiment showed that the proposed approach was successful with an accuracy of 95.1% and it outperforms several existing approaches in terms of Precision, Recall, F-measure, and Accuracy. CRL and MTL were added to boost feature sharing and representation learning, and the attention module and LSTM was added to help the model concentrate on clinically relevant patterns. Consequently, the framework was able to accurately categorize images into four classes: Healthy, Mild AA, Moderate AA, and Severe AA.

The overall proposed ADAR-Net can be considered as a useful computer-aided tool to assist in the diagnosis and severity assessment of Alopecia Areata. For future work, a larger and more diverse data set will be used to further extend the robustness and generalization ability of the framework. Moreover, more sophisticated data augmentation and feature enhancement methods can be explored, in order to improve the classification accuracy in real-world clinical settings.

6. Acknowledgement

This Work is acknowledged under Integral University manuscript No.IU/R&D/2026-MCN0004918.

REFERNCES

1. Kim, S., Shin, S., Kim, S. N., & Na, Y. (2021). Understanding the characteristics of the scalp for developing scalp care products. *Journal of Cosmetics, Dermatological Sciences and Applications, 11*(3), 204–216.https://doi.org/10.4236/jcdsa.2021.113018
2. Chang, W. J. J., Chen, L. B. B., Chen, M. C. B., Chiu, Y. C. C., & Lin, J. Y. Y. (2020). Scalp Eye: A deep learning-based scalp hair inspection and diagnosis system for scalp health. *IEEE Access, 8*, 134826–134837. https://doi.org/10.1109/ACCESS.2020.3010847
3. Alshahrani, A. A., Al-Tuwaijri, R., Abuoliat, Z. A., Alyabsi, M., Aljasser, M. I., &Alkhodair, R. (2020). Prevalence and clinical characteristics of alopecia areata at a tertiary care center in Saudi Arabia. *Dermatology Research and Practice, 2020*, 1–4. https://doi.org/10.1155/2020/7194270
4. Fricke, A. C. V., & Miteva, M. (2015). Epidemiology and burden of alopecia areata: A systematic review. *Clinical, Cosmetic and Investigational Dermatology, 8*, 397–403. https://doi.org/10.2147/CCID.S53985
5. Ocampo-Garza, J., & Tosti, A. (2019). Trichoscopy of dark scalp. *Skin Appendage Disorders, 5*(1), 1–8. https://doi.org/10.1159/000488885
6. Elder, A., Ring, C., Heitmiller, K., Gabriel, Z., & Saedi, N. (2021). The role of artificial intelligence in cosmetic dermatology: Current, upcoming, and future trends. *Journal of Cosmetic Dermatology, 20*(1), 48–52. https://doi.org/10.1111/jocd.13797
7. Alarcón-Soldevilla, F., Hernández-Gómez, F. J., García-Carmona, J. A., Carreño, C. C., Grimalt, R., Vañó-Galván, S., et al. (2021). Use of artificial intelligence as a predictor of the response to treatment in alopecia areata. *iProceedings, 7*(1), e35433. https://doi.org/10.2196/35433
8. Nie, Y., Sommella, P., Carratu, M., Ferro, M., O'Nils, M., & Lundgren, J. (2022). Recent advances in diagnosis of skin lesions using dermoscopic images based on deep learning. *IEEE Access, 10*, 95716–95747. https://doi.org/10.1109/ACCESS.2022.3199613
9. Lee, S., Lee, J. W., Choe, S. J., Yang, S., Koh, S. B., Ahn, Y. S., et al. (2020). Clinically applicable deep learning framework for measurement of the extent of hair loss in patients with alopecia areata. *JAMA Dermatology, 156*(9), 1018–1020. https://doi.org/10.1001/jamadermatol.2020.2188
10. Ibrahim, S., Azmy, Z. A. N., Mangshor, N. N. A., Sabri, N. N., Fadzil, A. F. A., & Ahmad, Z. (2020). Pre-trained classification of scalp conditions using image processing. *Indonesian Journal of Electrical Engineering and Computer Science, 20*(1), 138–144. https://doi.org/10.11591/IJEECS.V20.I1.PP138-144
11. Zhang, L., Man, Q., & Cho, Y. I. (2021). Deep-learning-based hair damage diagnosis method applying scanning electron microscopy images. *Diagnostics, 11*(10), 1831. https://doi.org/10.3390/diagnostics11101831
12. Chen, X., Li, X., Chen, B., Yin, Y., Zhang, J., & Zhou, C. (2021). Female pattern hair loss in female and male: A quantitative trichoscopic analysis in Chinese Han patients. *Frontiers in Medicine, 8*, 649392. https://doi.org/10.3389/fmed.2021.649392
13. Shakeel, C. S., Khan, S. J., Chaudhry, B., Aijaz, S. F., & Hassan, U. (2021). Classification framework for healthy hairs and alopecia areata: A machine learning approach. *Computational and Mathematical Methods in Medicine, 2021*, 1102083. https://doi.org/10.1155/2021/1102083
14. Gao, M., Wang, Y., Xu, H., Xu, C., Yang, X., Nie, J., et al. (2022). Deep learning-based trichoscopic image analysis and quantitative model for predicting basic and specific classification in male androgenic alopecia. *Acta Dermato-Venereologica, 102*, adv00564. https://doi.org/10.2340/actadv.v101.564
15. Kim, M., Kang, S., & Lee, B. D. (2022). Evaluation of automated measurement of hair density using deep neural networks. *Sensors, 22*(2), 650. https://doi.org/10.3390/s22020650
16. Jeong, J. I., Park, D. S., Koo, J. E., Song, W. S., Pae, D. J., & Choi, H. J. (2022). Artificial intelligence (AI)-based system for the diagnosis and classification of scalp health: AI-ScalpGrader. *Instrumentation Science & Technology*, 1–11. https://doi.org/10.1080/10739149.2022.2129382
17. Roy, M., & Protity, A. T. (2023). Hair and scalp disease detection using machine learning and image processing. *European Journal of Information Technologies and Computer Science, 3*(1), 1–7. https://doi.org/10.48550/arXiv.2301.00122.
18. Khan, S., & Abbas, S. H. (2026). Enhancing cloud data security with a robust intrusion detection system based on machine learning. *Scientific Culture, 12*(4), 5781–5794. https://doi.org/10.5281/zenodo.19580733.
19. Khan, S., & Abbas, S. H. (2025). Enhancing Cloud Data Security using a Hybrid Cryptographic Model: A Combination of Advanced Encryption Standard and Elliptic Curve Cryptography. Journal of Information Systems Engineering and Management, 10(34s), 1-13. e-ISSN: 2468-4376.
20. Verma, N. K., & Sadia, H. (2025). A Comprehensive Review of Alopecia Areata Detection Using Self-Supervised Auto ML Models: Systematic Insights and Emerging Challenges. 2025 7th International Conference on Information Systems and Computer Networks, ISCON 2025, 1–4. https://doi.org/10.1109/ISCON65210.2025.11341386.

21. Faisal, M., Sadia, H., Ahmed, T., & Javed, N. (2022). Blockchain Technology for Healthcare Record Management. Pervasive Healthcare: A Compendium of Critical Factors for Success, 255-286.
22. Sadia, H., Abbas, S. Q., & Faisal, M. (2022). A Bayesian network-based software requirement complexity prediction model. In Computational Methods and Data Engineering: Proceedings of ICCMDE 2021 (pp. 197-213). Singapore: Springer Nature Singapore.