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Multi-Class Support Vector Machine Classification for Detecting Alopecia Areata and Scalp Diseases

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Abstract— Alopecia Areata is a health condition marked by the absence of hair in specific regions, such as the scalp, face, and parts of the body. It occurs due to an autoimmune reaction where the body's immune system erroneously targets the hair follicles, leading to irregular hair loss patterns. It can affect people of all ages, genders, and ethnicities, and it is estimated to affect about 2% of the population worldwide. Timely identification and precise diagnosis of this condition are crucial in order to implement effective treatment strategies. The most common type of alopecia is alopecia areata (AA), which is typically detected and diagnosed using medical image processing models. In this study, we describe a unique method for image processing that incorporates a multiclass support vector machine classification approach. Our proposed methodology aims to attain accurate detection and categorization of a wide range of scalp issues, encompassing Alopecia Areata and other related conditions. The proposed approach entails capturing images of individuals with alopecia disease, enhancing the quality of the images through preprocessing techniques, and extracting distinctive features from scalp images using a range of image processing methods. Next, the extracted features are fed into a Multi-class SVM classifier, and a machine learning model is trained to achieve precise classification of the various conditions associated with alopecia areata. The evaluation of the proposed method using hair and scalp image databases demonstrates that the Multi-class SVM model achieves an accuracy of 89.3%, outperforming other models in terms of classification accuracy.

Keywords- Scalp conditions, Machine Learning, Image processing ,Alopecia Areata, Support Vector Machine.

I. INTRODUCTION

The way hair looks are highly important in how people see themselves and express their own unique identity. Hair Loss, known as alopecia, is often associated with a loss of influence and domaince [1] and can be caused by a variety of factors such as stress, bad daily routines, unbalanced weight gain, fatigue and exposure to toxins in the environment [2]. Baldness can result from at least 30% of scalp issues. Ra put has investigated how air contamination causes baldness and its medical manifestations [3]. As per the World Health Organization (WHO), around 70% of people encounter issues pertaining to the health and condition of their scalp hair, which can be attributed to factors such as endocrine imbalances, genetic factors, underlying illnesses, and other internal variables [4]. Even children can experience scalp issues, such as psoriasis, which affects about 18% of children in the USA and Australia [5-6]. Therefore, it is crucial to know how to prevent baldness associated disorders and maintain healthy scalp conditions. Specific treatments like Hair Physio have been developed to treat severe scalp disorders in recent years.

It is usual practice during the evaluation of baldness treatments to check the condition of a patient's scalp through manual examination. Nonetheless, this method is heavily reliant on the proficiency and expertise of the physiotherapist, which can lead to varying outcomes and create uncertainties regarding the accuracy of the diagnosis. Hair care procedures face two major challenges, including enhancing the physiotherapy skill set and the discrepancies in the interpretation of scalp hair microscope pictures. To overcome these challenges, a smart scalp detection model, ScalpEye [8], has been developed using deep learning technology to diagnose frequent scalp problems such as psoriasis, cellulitis, baldness, and greasy hair. Approximately 2% of the population is affected by Alopecia Areata (AA), which is a common scalp disorder [9].

The sudden non-scarring hair loss disorder [10], Alopecia Areata (AA), can appear in different forms, including small patches or more widespread irregular involvement [11]. In recent years, several scalp and dermoscopic images have been used for AA diagnosis, but traditional diagnostic techniques like biopsies and tracheoscopies may require multiple tests for an accurate diagnosis [12]. Thus, there is a need for further research on AI models like machine learning and DL approaches for AA recognition and diagnosis [13-15]. Several AI models, such as SVM, KNN, decision trees, ANN, and CNN, have been used in healthcare for diagnostic purposes. In dermatology and trichology, AI models have accurately diagnosed and predicted

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hair loss using healthy and AA hair images, but it is essential to recognize both AA and the scalp condition simultaneously for a proper diagnosis [16].

Thus, this scholarly article presents an approach that employs image processing techniques to detect and classify alopecia areata, with the primary objective of identifying and categorizing this particular condition. Our method consists of three stages preprocessing, feature extraction, and classification. In the preprocessing stage we apply noise reduction and segmentation techniques to isolate the hair and the scalp regions. Then in the feature extraction stage, we extract the feature such as texture, color, shape from the hair and scalp region using various image processing algorithms. In the final classification stage, we employ a Multi-Class Support Vector Machine (SVM) Classifier to categorize the images into different groups, namely healthy hair, mild, moderate, and severe.

The remaining sections are structured as follows: Section II focuses on investigating and classifying AA/scalp conditions. Section III elaborates on the proposed methodology, whereas Section IV showcases its effectiveness. Finally, Section V offers a concise overview of the study.

II. LITERATURE SURVEY

An intelligent system for detecting and addressing hair loss issues [17]. The system employs a rule based approach to identify the underlying causes of hair loss and recommend appropriate treatment options based on patient specific characteristics. The study highlights the promising potential of expert systems in supporting healthcare providers and individuals in the diagnosis and management of hair loss. However, the authors recognize the importance of conducting further research to validate the system's effectiveness in real-world clinical settings.

A system that utilizes machine learning methods to identify hair-covered areas on the scalp in medical images [18]. The authors utilized various machine learning techniques, including AdaBoost, decision tree, and random forest model, to train their system and achieved high level accuracy in identifying hairy scalp regions. The research illustrates the promise of employing machine learning approaches for the automated identification and treatment of scalp conditions. However, the authors note the need for further research to conform the performance of the system, on larger and more diverse datasets.

A new approach for analyzing trichoscopic images of patients with alopecia areata [19]. By employing grid line selection and eigenvalue computation, the authors were able to extract hair loss features and achieve a classification accuracy of 90.5%. The study highlights the potential of computer-aided analysis of trichoscopic images for the diagnosis and management of alopecia areata. However, the study's findings may be limited by the small dataset size, and further validation on larger datasets is necessary to evaluate the proposed method's effectiveness and generalizability

A hospital-based cross-sectional study were conducted to investigate the clinical, dermoscopic, and histopathological features of alopecia areata [20]. The study included 50 patients and showed that the condition was more prevalent among individuals aged 20-40 years, with a slightly higher incidence in females. The authors also identified specific dermoscopic findings and histopathological features associated with alopecia areata, which could aid in the accurate diagnosis and management of the condition. The authors suggest that further research is necessary to confirm their findings on a larger scale.

A deep learning method were used for classifying scalp conditions using pre-trained models [21]. Their approach achieved an accuracy of 98.5% in classifying scalp images into different conditions. The study highlights deep learning techniques for automating scalp condition diagnosis and monitoring. However, the small size of the dataset limits the study's generalizability, and further validation using larger and diverse datasets is needed to evaluate the model's performance. In summary, the research demonstrates the promising capabilities of machine learning techniques in the identification and treatment of scalp conditions

A deep CNN model that utilized SEM images to classify hair samples as undamaged, slightly damaged, or severely damaged [22]. The study yielded an impressive classification accuracy of 96.7%, signifying the potential of the proposed method as an automated hair damage diagnosis tool in clinical settings. The study emphasizes the efficacy of utilizing deep learning techniques and SEM images for hair damage assessment. However, the study's limited dataset size of only 150 SEM images is a constraint, and more comprehensive and diverse datasets are necessary to evaluate the model's performance and generalizability. Furthermore, the current method only accounts for surface damage on hair fibers, necessitating potential modifications to assess damage to the hair cuticle or cortex

Various studies have used different features and classifiers, such as SVM, KNN, and decision tree models, to distinguish between healthy hair and alopecia areata-affected hair [23]. The use of color and texture features has been identified as crucial in accurately diagnosing the disease. However, the studies are limited by small dataset sizes, ranging from 50 to 200 images, which hinder the generalizability of the proposed frameworks. Hence, additional verification using larger and more varied datasets is required to evaluate the effectiveness and applicability of the machine learning models

To investigate the accuracy of using deep neural networks to measure hair density compared to manual methods [24]. The dataset used for training the algorithm consisted of images from patients with androgenetic alopecia and healthy controls, and high agreement with manual measurements was observed. The

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authors propose that this automated approach could offer a more efficient and objective way to evaluate hair density in clinical settings and research. Nevertheless, the research does have certain limitations, including a limited sample size and the necessity for additional validation in broader and more diverse patient populations. The algorithm may also not account for variations in hair thickness and texture. Despite these limitations, the study demonstrates the potential of deep neural networks to automate hair density measurements, which could have significant implications for improving the diagnosis and management of hair loss conditions.

III. PROPOSED METHODOLOGY

We will outline the suggested system's technique in this part, which is aimed for the preprocessing and categorization of images of alopecia areata. The primary objective of this system is to accurately identify normal hair and categorize alopecia areata cases into mild, moderate, or severe stages. The entire architecture of the system can be segmented into several modules, encompassing preprocessing, enhancing image quality, segmenting images, extracting relevant features, and performing classification. Through the utilization of these modules, our system can accomplish precise and reliable alopecia areata detection and classify the available images. Fig 1. presents the components in the block diagram depicting the proposed system.

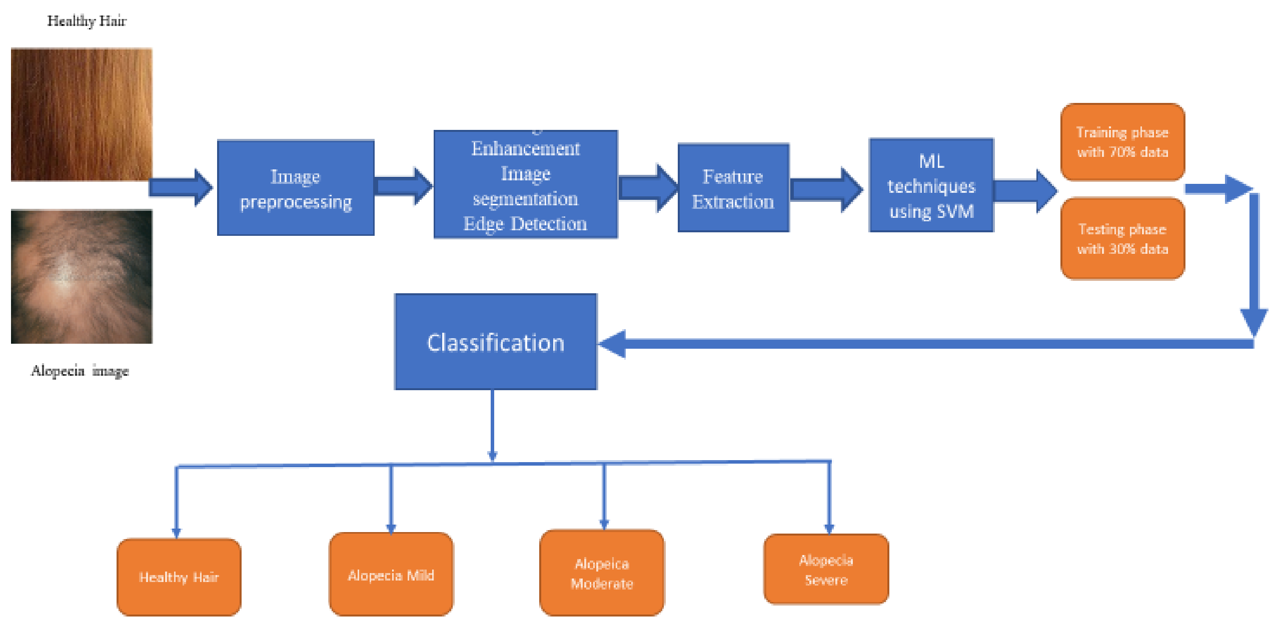

Figure 1. The proposed system block diagram

A. *Image Acquisition*

In this study, 2 different publicly available databases are gathered and they are:

1. Figaro1k database: It is an open database comprising 1050 hair images, equally distributed in various classes like straight, wavy and curly [25].
2. Dermnet database: A publicly accessible database, contains a wide range of dermatological disorders classified into 23 different categories, including alopecia areata (AA) [26]. For the purpose of this study, a subset of the database was employed, comprising a total of 108 images that were specifically selected to represent three distinct classes of AA: mild, moderate, and severe.

The hair and scalp images collected from these databases are given to the Multi Class SVM for AA scalp conditions classification. Some example images of scalp hair and alopecia areata from the datasets are shown in Fig. 2.

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B. Preprocessing

After acquiring the scalp hair image archives, a series of preprocessing techniques are implemented to improve the enhanced caliber of the images and extract meaningful features. These techniques include image enhancement, segmentation, and edge detection, which collectively contribute to enhancing the overall quality and extracting relevant features from the images.

Figure 2. Images of the scalp hair and alopecia areata

1) Image Enhancement

The main goal of image enhancement techniques is to elevate the overall excellence of an image by enhancing its contrast, brightness, and luminance values of pixels. These techniques are specifically designed to adjust the image's characteristics, resulting in a visually enhanced image that is both visually appealing and suitable for easier analysis. This, in turn, facilitates subsequent processing and analysis tasks related to the image. The system employs the Histogram Equalization (HE) method as the initial step to enhance the given scalp hair images. This method improves areas with poor local contrast by increasing the intensities, thereby enhancing the global contrast. The RGB image is converted into an HSV representation, which includes hue, saturation, and value components. Subsequently, the intensity values of the image are modified using a histogram, leading to an enhancement in the visual quality of the image. Fig. 3. Before applying histogram equalization, the provided sample image of alopecia areata exhibits poor local contrast. However, after the application of histogram equalization, the intensities are increased, as a result of this process; there is a significant improvement in the overall contrast of the image. This enhancement can be observed in the before-and-after comparisons of the image.

Figure 3. Before and after histogram Equalization

2) Image Segmentation

Image segmentation involves dividing image pixels into segments with similar characteristics like texture and intensity. This grouping helps analyze and understand the image better. Image segmentation involves the utilization of two key techniques: resizing and edge identification, to achieve its goal. In the resizing process, the dimensions of the image are reduced by applying a scaling factor. For instance, if the scaling factor is set to 64, the segmented output image will have dimensions scaled down by a factor of 64. This means that the resulting image will be smaller in size compared to the original. Edge identification is a fundamental step in image segmentation, where the primary objective is to locate curves within an image that exhibit a distinct pattern characterized by rapid fluctuations in contrast or brightness of the images. Additionally, the images' jagged or rough edges are rounded off using an antialiasing method. As a result, all the images of scalp hair are subjected to preprocessing and enhancement utilizing these techniques. Fig 4. demonstrating before and after image of alopecia areata edge detection.

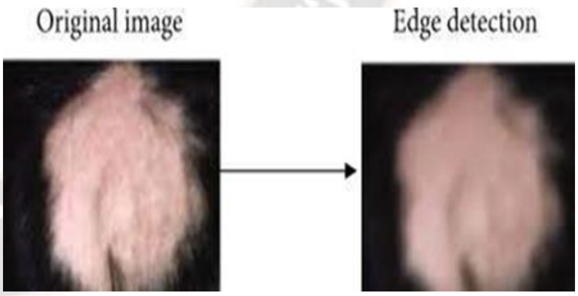

Figure 4. Before and after edge detection

C. Feature Extraction

Feature extraction is an important aspect of image classification as it aims to capture relevant information from an image that can be utilized to determine its significance. The process involves extracting distinctive characteristics such as shape, color, and texture, which are widely employed in various image processing techniques. By extracting and incorporating color, shape, and texture features, image classification algorithms can achieve higher accuracy. These features contribute to a more comprehensive representation of the

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image, facilitating more precise analysis and decision-making in various applications.

Color feature: By computing the color features for all blocks in image, it is possible analyze the overall color content and distribution of image and extract the meaningful information of scalp images Color moments are associated with the idea that the way colors are spread across scalp hair images can be expressed through a probability distribution. By analyzing these statistical moments, we can identify unique features that facilitate the classification of scalp hair images based exclusively on their color, assuming that the color distribution in the image adheres to a specific probability model. Color moment data consists of four groups of statistical measurements: (i) the average color value, which represents the mean color, (ii) the standard deviation, which describes the spread or range of the color distribution, (iii) the skewness, which indicates the degree of asymmetry in the color distribution, and (iv) the kurtosis, which characterizes the shape of the color distribution by measuring its flatness or curvature. Such 4 color moments are given in the Eq. (1) to Eq. (4)

$$\mu_C = \frac{1}{WH}\sum_{i=1}^{W}\sum_{j-1}^{H} P_{ij}^{C} \tag{1}$$

$$\sigma_C = \sqrt{\frac{1}{WH}\left(\sum_{i=1}^{W}\sum_{j-1}^{H}\left(P_{ij}^{C}-\mu_C\right)^2\right)} \tag{2}$$

$$\theta_C = \sqrt[3]{\frac{1}{WH}\left(\sum_{i=1}^{W}\sum_{j-1}^{H}\left(P_{ij}^{C}-\mu_C\right)^3\right)} \tag{3}$$

$$\gamma_C = \sqrt[4]{\frac{1}{WH}\left(\sum_{i=1}^{W}\sum_{j-1}^{H}\left(P_{ij}^{C}-\mu_C\right)^4\right)} \tag{4}$$

Shape feature: Moment invariants are a collection of mathematical characteristics that can be derived from images. These moment variants consist of seven distinct values, which remain unchanged regardless of transformations such as scaling, resizing, and rotation. These invariant features are valuable for extracting shape-related information from a dataset of images.

If we define a scalp hair image as $f(x,y)$, then the $i+j$ order moment of the image can be represented as

$$M_{ij} = \sum_x \sum_y x^i y^j f(x,y), \forall i,j = 0,1,\ldots \tag{5}$$

Following that Eq. (6), the central moment is given by

$$\delta_{i,j} = \sum_x \sum_y (x-\bar{x})^i (y-\bar{y})^j f(x,y) \tag{6}$$

In Eq. (6), $\bar{x} = \frac{M_{10}}{M_{00}}$, $\bar{y} = \frac{M_{01}}{M_{00}}$. The standardized $i+j$ order central moment can be calculated in Eq. (7)

$$:\eta_{i,j} = \frac{\delta_{i,j}}{\delta_{00}^{\left(\frac{i+j}{2}\right)+1}} \tag{7}$$

Moreover, the 7 moment invariants are determined by

$$h_0 = \eta_{20} + \eta_{02}$$

$$h_1 = (h_0)^2 + 4\eta_{11}^2$$

$$h_2 = (\eta_{30} + 3\eta_{12})^2 + (3\eta_{21} + \eta_{03})^2$$

$$h_3 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$h_4 = (\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$

$$+3(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$h_5 = (\eta_{20} + \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$+4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$h_6 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$

$$+(\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03}) \times [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{8}$$

Texture features: Texture features are used to quantify the visual pattern and characteristics of an image which can be used to identify the healthy hair and scalp images. In GLCM, the Co-occurrence of pairs of pixel values at a specific distance and orientation in an image is computed. This result in a matrix that captures the spatial relations ship between pixel in the image. The GLCM can be utilized to extract texture features from an image, encompassing contrast, correlation, energy, and homogeneity. These features can be calculated at different angles, namely 0°, 45°, 90°, and 135°. By considering these angles, distinct aspects of the image's texture are captured, resulting in a holistic portrayal of its texture properties.

$$Contrast = \sum_{n=0}^{N_g-1} n^2 \left\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\right\}, |i-j| = n \tag{9}$$

$$Correlation = \frac{\sum_i \sum_j (ij)p(i,j) - (\mu_i \mu_j)}{\sigma_i \sigma_j} \tag{10}$$

$$Energy = \sum_{ij} p(i,j)^2 \tag{11}$$

$$Homogeneity = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \tag{12}$$

In Eqns. (9) and (12), the variable $p(i,j)$ represents the joint probability distribution of a pair of pixels. It indicates the likelihood of encountering one pixel with gray level i and

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another pixel with gray level j. The value of Ng is used to define the number of gray levels considered in generating the Gray-Level Co-occurrence Matrix (GLCM). Additionally, the symbols μ_i, μ_j, σ_i and σ_j correspond to the mean and standard deviations of the marginal distributions associated with $p(i, j)$. These values can be calculated in Eqn. (13) to Eqn. (16) as follows:

$$\mu_i = \sum_{i,j=0}^{N_g-1} i(\mathcal{P}_{i,j}) \tag{13}$$

$$\mu_j = \sum_{i,j=0}^{N_g-1} j(\mathcal{P}_{i,j}) \tag{14}$$

$$\sigma_i = \sum_{i,j=0}^{N_g-1} \mathcal{P}_{i,j}(i - \mu_i) \tag{15}$$

$$\sigma_j = \sum_{i,j=0}^{N_g-1} \mathcal{P}_{i,j}(j - \mu_j) \tag{16}$$

D. Classification

Multiclass SVM classification using Support Vector Machines(MSVM) is an extension of binary SVM classification to handle problems with multiple classes. The classification techniques used to classify the healthy hair and alopecia disease. Scalp conditions are classified using the Multi Class Support Vector Machine (MSVM) technique. MSVM is a powerful classifier widely used for data analysis and identifying patterns. It excels in categorizing data by leveraging statistical patterns, making it a valuable tool in the classification of scalp conditions. Extract relevant features from the preprocessed scalp images. This can include color, shape, and texture features. If the extracted feature set is high-dimensional, you may consider performing feature selection techniques to reduce dimensionality and remove irrelevant features. This can help improve the efficiency and performance of the classification process. Multiclass SVM model using the training dataset. Choose an appropriate kernel such as linear and set the SVM to perform multiclass classification using techniques like one-vs-one or one-vs-all. Adjust the hyperparameters based on the validation set to achieve the best performance. Finally, classification stage classifier to classify the images in categories healthy hair, mild, moderate, severe alopecia areata. Table 1 shows the performance values for existing and proposed AA classification and diagnosis models during the testing phase.

Table 1 Performance analysis of existing and proposed AA Classification and diagnosis model

Models	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
KNN	69.58	68.24	69.07	68.66
HDM-Net	75.49	74.26	75.11	74.69
YoloV4	80.65	79.48	80.22	79.85
MSVM	87.68	87.82	87.24	87.53

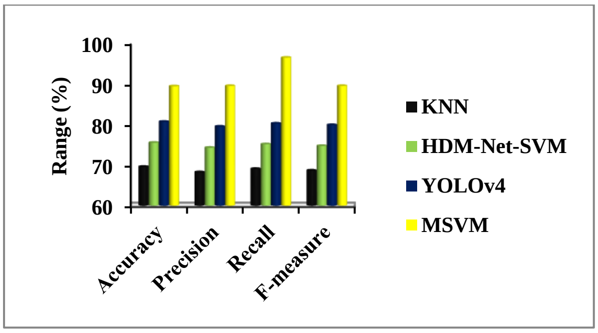


Figure 5. Performance analysis of existing and proposed AA Classification and diagnosis model

Fig. 5 presents the evaluation results of different classification models applied to the Dermnet and Figaro1k databases, with metrics including accuracy, precision, recall, and f-measure. It addresses that the accuracy of the MSVM is 19.8% higher than the KNN, 13.89% higher than the HDM-Net-SVM, and 8.73% higher than the YOLOv4 models. The precision of the SVM is 21.2% higher than the KNN, 15.2% higher than the HDM-Net-SVM, and 9.98% higher than the YOLOv4 models. The recall of the SVM is 27.3% higher than the KNN, 21.3% higher than the HDM-Net-SVM, and 16.2% higher than the YOLOv4 models. Also, the f-measure of the SVM is 20.8% higher than the KNN, 14.7% higher than the HDM-Net-SVM, and 9.61% higher than the YOLOv4 models due to the capturing local features at different scales within the given ROIs of the hair and scalp images for AA classification.

IV. RESULTS AND DISCUSSION

In this section, the efficacy of the MSVM model is investigated by implementing it in MATLAB 2017b and utilizing the figaro1k and Dermnet databases. The experiment adopts a data splitting methodology, where 70% of the images are allocated for training the model, while the remaining 30% of images are utilized for testing and assessing the performance of the trained model. Additionally, a comparative analysis is presented to demonstrate its effectiveness compared with the classical models such as KNN [23], HDM-Net [22], and YOLOv4 [25] based on the different evaluation metrics. Fig. 6 shows selection of sample scalp hair images from the analyzed databasesfor various classes.

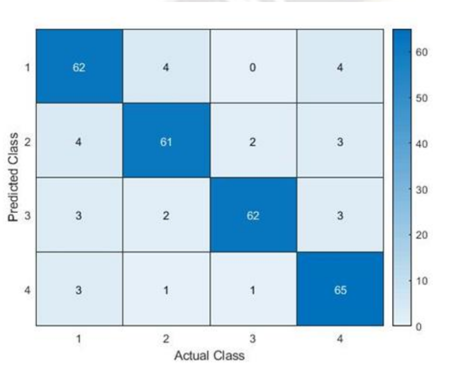
Moderate Alopecia (2)

Severe Alopecia (3)

Figure 6. Sample images of Scalp Hair representing various categories

Table 2. display the confusion matrices illustrating the performance of the MSVM model on the selected test images.

Table 2 The confusion matrix for the testing stage of the MSVM model



A. Performance Metrics

Accuracy: It is the proportion of precise identification over the total images analyzed.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \quad (17)$$

In Eq. (17), TP (true positive) represents the count of correctly identified healthy pictures classified as healthy, while TN (true negative) signifies the count of correctly identified AA (alopecia areata) pictures classified as AA. FP (false positive) corresponds to the count of AA pictures erroneously identified as healthy, and FN (false negative) represents the count of healthy pictures mistakenly identified as AA.

Precision is calculated by:

$$Precision = \frac{TruePositive}{True\ Positive + False\ Positive} \quad (18)$$

Recall is calculated by:

$$Recall = \frac{TruePositive}{True\ Positive + False\ Negative} \quad (19)$$

F-measure is determined as:

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (20)$$

V. CONCLUSION

In this study, the SVM model was presented for identifying and diagnosing various levels of AA by learning both hair and scalp images together. Primarily, the hair and scalp image databases were acquired from the openly available sources. Therefore in this study, we propose detecting alopecia areata and scalp diseases through image processing and Multi-Class Support Vector Machine Classification. Our method consists of three stages preprocessing, feature extraction, and classification. In the preprocessing stage we apply noise reduction and segmentation techniques to isolate the hair and the scalp regions. Then in the feature extraction stage, we extract the feature such as texture, color, shape from the hair and scalp region using various image processing algorithms. Finally, classification stage we use a Multi class support vector machine (MSVM) Classifier to classify the available images in categories healthy hair, mild, moderate, severe alopecia areata. The final accuracy achieved for AA identification and diagnosis is 89.3%, surpassing the performance of other models. As a result, it supports physicians to diagnose patients who suffer from AA earlier.

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