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Pre-trained classification of scalp conditions using image processing

Shafaf Ibrahim, Zarith Azuren Noor Azmy, Nur Nabilah Abu Mangshor, Nurbaity Sabri, Ahmad Firdaus Ahmad Fadzil, Zaaba Ahmad
[1]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Malaysia

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ABSTRACT

Scalp problems may occur due to the miscellaneous factor, which includes genetics, stress, abuse and hair products. The conventional technique for scalp and hair treatment involves high operational cost and complicated diagnosis. Besides, it is becoming progressively important for the payer to investigate the value of new treatment selection in the management of a specific scalp problem. As they are generally expensive and inconvenient, there is an increasing need for an affordable and convenient way of monitoring scalp conditions. Thus, this paper presents a study of pre-trained classification of scalp conditions using image processing techniques. Initially, the scalp image went through the pre-processing such as image enhancement and greyscale conversion. Next, three features of color, texture, and shape were extracted from each input image, and stored in a Region of Interest (ROI) table. The knowledge of the values of the pre-trained features is used as a reference in the classification process subsequently. A technique of Support Vector Machine (SVM) is employed to classify the three types of scalp conditions which are alopecia areata (AA), dandruff and normal. A total of 120 images of the scalp conditions were tested. The classification of scalp conditions indicated a good performance of 85% accuracy. It is expected that the outcome of this study may automatically classify the scalp condition, and may assist the user on a selection of suitable treatment available.

Corresponding Author:

Shafaf Ibrahim,
Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA,
Melaka Branch Jasin Campus,
77300 Merlimau, Melaka, Malaysia.
Email: shafaf2429@uitm.edu.my

1. INTRODUCTION

The scalp is a special skin zones in humans, with high follicular thickness and a high rate of sebum creation. Sebum is unique in some aspects and differs in composition with other lipids [1]. Hair is also playing an important role in the appearance and the function is to protect from heat conservation, and improvements of appearance which affect self-esteem and social trust. Hair is often associated with identity, and its significance goes beyond the surface. It has psychological, social, and sometimes spiritual meaning [2].

Scalp problems happen in some factors which are stress, abuse of hair products, for instance, straighteners, waves, and dyes as may cause contact allergic, chemical burns, and increased hair breakage. A related acute generalized disease, personal past history of chronic systemic disease, and the use of other drugs can all be related to scalp problems [3]. The excessive or prolonged chemical treatment, grooming habits, and exposure to the environment could result in changes in hair texture and, where severe, hair breakage [4]. There are also records that environmental changes could cause hair loss too. Most cases of hair's breadths due to changes in the hair cycle rather than to hair scape mat, whereas it is the hair shaft that is affected by hair merchandise, either favourably or adversely [3]. The scalp and hair are subject to the both essential ingredients of physiologic senescence, as well as extrinsic factors of premature senescence due to the external environment [5].

The most common type of scalp problem conditions experienced by the human are alopecia areata (AA), dandruff, pediculosis capitis, and seborrheic dermatitis. There are several putative causes including non-microbial and microbial factors. Persistent and relapsing scalp syndrome is dandruff that may affect about half the world's population, regardless of gender and ethnicity [6]. The dandruff is usually defined as excessive flaking of the scalp and in the hair and is often accompanied by itch [7].

On the other hand, the AA can be classified by the extent or pattern of loss of hair [8]. It was assumed that the AA is an organ-specific autoimmune illness with a genetic predisposition and an environmental trigger [9]. The localized, non-scarring hair loss, and an auto immune skin disease is the hair follicle that is the target of an immune attack is a common form of AA [10]. According to [11], the AA is the most mutual cause of inflammatory−induced alopecia in the United States (US), occurring equally in African-Americans and Caucasians. The AA demonstrates this condition due to its significant burden of disease and its often-devastating effects on the quality of life and the patient's self-esteem [12].

Yet, the conventional technique for scalp and hair treatment involves a complicated diagnosis. Many commons scalp pre-condition has similar symptoms and clinical features, complicated diagnosis, nevertheless a correct diagnosis is the key to proper treatment. Practical solutions for improving the treatment of hair patients include the accumulation of issues over multiple visits to allow enough time to address patient concerns [13]. Additional complicated diagnoses may include melanin in the fibrous nerve pathway in AA, and even the pigment type may be known, especially in people with dark hair [14].

Additionally, the scalp treatment implies a high operational cost too. Thus, it is becoming progressively important for the payer to investigate the value of new treatment selection in the management of scalp conditions [15]. As they are typically costly and inconvenient, an inexpensive and convenient way of monitoring scalp condition is increasingly needed [16].

Image processing is a recent advance in computer graphics. Image processing has made it possible to accurately reconstruct a photograph on a high-resolution computer screen almost instantaneously. Today, the image processing technique is conveniently used in all areas of science [17], satellite images, industrial applications and medical [18].

Thus, based on the problem discussed it is necessary to initiate an alternative technique to classify the scalp conditions automatically. Thus, a study of pre-trained classification of scalp conditions using image processing technique is proposed. The organization of the remainder of this paper is as follows: Section 2 provides our methods, including an overview of the methodology, and the description of algorithm structure. Our results and discussions are discussed in Section 3. Finally, in Section 4, we present our conclusion.

2. RESEARCH METHOD

The aim of this study is to classify the scalp conditions using the Support Vector Machine (SVM), and to evaluate the pre-trained classification of scalp conditions performance. Figure 1 portrays the proposed process flow of the pre-trained classification of scalp conditions.

The proposed process flow of pre-trained classification of scalp condition begins with the input image which is the scalp. The image will then go through the image enhancement process to get rid of the unwanted distortion. The color feature extraction is performed on the enhanced images. The enhanced images are converted to the greyscale before the texture feature extraction is performed as it is used to simplify and reduce the computational requirements. Next, the edge detection process is done on the grayscale images in order to allow the extraction of the shape features. The properties of three features of color, texture, and shape were extracted from each input image, and stored in a Region of Interest (ROI) table. The knowledge of the values of the pre-trained features is used as a reference in the classification process subsequently. The classification is used to classify the type of scalp conditions to which the image belongs. After the image is classified, the system will produce the final result which is the scalp condition classification.

2.1. Scalp image

A total of 120 images of the scalp conditions were collected. The three types of the scalp condition are alopecia areata (AA), dandruff, and normal scalp. Table 1 tabulates the sample images of the scalp conditions as mentioned.

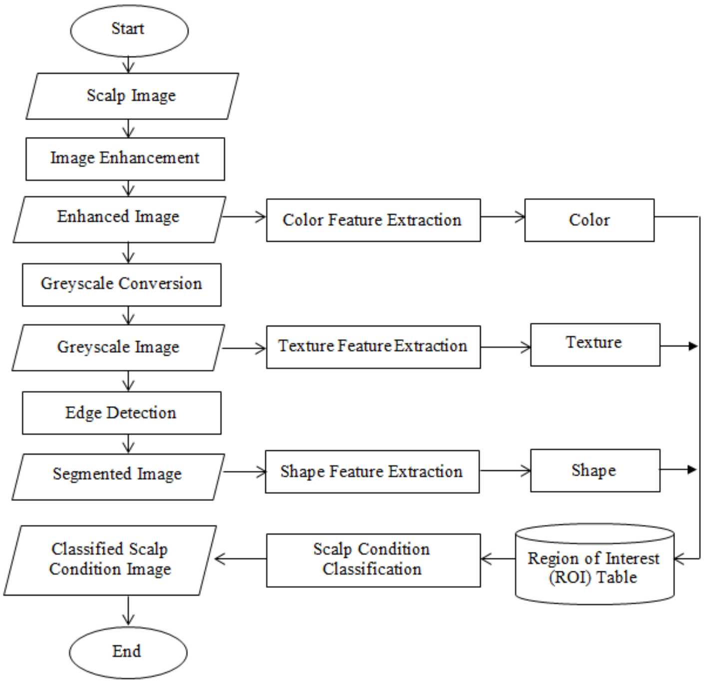


Figure 1. Proposed flowchart of scalp problem recognition

Table 1. Sample images of scalp conditions

Type	Image
Alopecia Areata (AA)	
Dandruff	
Normal	

2.2. Image enhancement

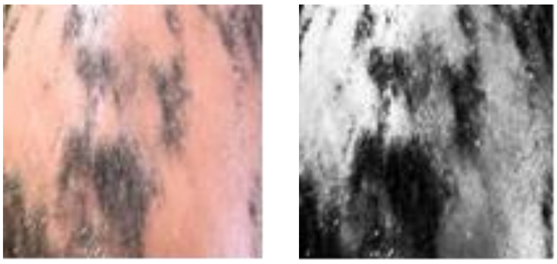
Image enhancement is the change of the image by converting the pixel luminance values to improve its visual impact [19]. It is done on the gathered images for improving the image quality [20], and it could be a method to get rid of the unwanted distortion thanks to deterioration [21]. In this study, the Histogram Equalization (HE) is employed. The HE is a technique that improved a color of the image contrast and it is a straightforward method for enhancing the image quality [22]. It is also best known for changing the mean brightness of the enhanced image, where the mean brightness of the image input is significantly changed from the resulting image. [23]. Figure 2 depicts the sample of outcomes of image enhancement.

Before HE enhancement After HE enhancement

Figure 2. Sample outcomes of HE images enhancement

2.3. Greyscale conversion

Grayscale conversion is an approach in transforming an image into dim or gray based color as the result [24]. The process of converting a color to a grayscale image interpreted as a mapping or projection of a higher vector space into a lower-dimensional space [25]. The greyscale converted image could be utilized in many applications of completely different fields effectively [26]. Figure 3 shows the different between before and after the greyscale conversion is performed.



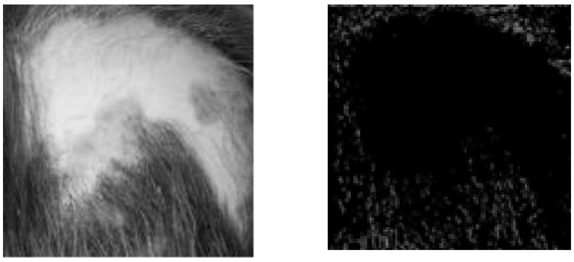
Before conversion After conversion

Figure 3. Greyscale conversion

2.3. Edge detection

Segmentation refers to a process of dividing an image into meaningful regions or objects [27]. The segmentation approach is used to achieve a more accurate result before further processes such as recognition, classification or other identification are performed [28]. Edge detection is one of the segmentation techniques in which the approach most generally used for detecting edges within the intensity of image [29].

In this study, the edge detection process is done on the grayscale images in order to allow the extraction of the shape feature properties. The Sobel technique is implemented for this purpose. The Sobel operator operates by measuring the gradient of each element's brightness intensity, giving the direction of the greater potential increase from black to white, and additionally calculating the amount of change in that direction [30]. Figure 4 illustrates sample images of Sobel edge detection.



Before edge detection After edge detection

Figure 4. Sobel edge dtection

2.4. Feature extraction

Image features extraction is an essential stage that utilizes algorithms and techniques to identify and isolate different sections or characteristics of a given image [31]. In this feature extraction stage, a total of 10 properties of three features of color, texture, and shape were extracted from each input image, and stored in a Region of Interest (ROI) table. The technique that has been used for the color, texture, and shape feature extraction are Color Moment, Gray Level Co-Occurrence Matrix (GLCM), and Regionprops accordingly.

Colour is one of the most widely used features. It is also the first and one of the most widely used visual features in image retrieval and indexing [32]. The Colour Moment technique provides a measurement of colour similarity between images [33]. It is accustomed to distinguish image on the premise of their color options. The three-color properties extracted are mean red, mean green, and mean blue.

On the other hand, a texture is a significant feature that captures the recent object in any image. The spatial distribution of the pixels near an image makes the texture clearer. It characterizes texture by generating statistics of the intensity distribution as well as the location and orientation of similarly valued pixels [34]. The GLCM technique is found to be the most appropriate technique to be used due to its speed and less complexity. The four suitable GLCM texture properties extracted are contrast, correlation, energy and homogeneity [35].

Shape is an important cue for recognition as humans can often recognize characteristic of objects merely on the basis of their shapes. The Regionprops function by Matlab is employed to extract the feature of conic regions in an image of perform, particularly for the characterization of the orientation of the conic regions [36]. It is to ration the region properties in an image and reappearance them as a structured array [37]. It is effective in many object recognition applications and is rather efficient in computation. There are three Regionprops shape properties extracted which are area, major length axis and minor length axis.

Next, the 10 properties of color, texture, and shape extracted from all the images are stored in a ROI table. The knowledge of the values of the pre-trained features is used as a reference in the classification process subsequently. Table 2 tabulates the ROI table produced from the feature extraction process of scalp conditions images.

Table 2. ROI table

Type of Scalp Condition	Feature properties		Range Value
Alopecia Areata (AA)	Color	Mean Red	129.566-200.247
		Mean Green	82.383-139.862
		Mean Blue	60.721-130.12
	Texture	Contrast	24.3587-3396.99
		Correlation	0.607236-0.997313
		Energy	0.000104585-9.22461
		Homogeneity	0.0895999-0.553896
	Shape	Area	1.12562-386284
		Major Axis	144.338-3491.81
		Minor Axis	101.614-2327.88
Dandruff	Color	Mean Red	133.135-169.959
		Mean Green	109.333-133.872
		Mean Blue	0.71-131.301
	Texture	Contrast	4.4669-3587.24
		Correlation	0.6007-0.933709
		Energy	0.000108172-8.50067
		Homogeneity	0.0691-0.207285
	Shape	Area	1.31808-1177056
		Major Axis	185.907-287280
		Minor Axis	166.277-68904
Normal	Color	Mean Red	125.697-188.517
		Mean Green	89.863-142.996
		Mean Blue	64.442-135.006
	Texture	Contrast	55.8271-3144.61
		Correlation	0.689855-0.994537
		Energy	0.000115807-9.7932
		Homogeneity	0.0962138-0.457836
	Shape	Area	1.87488-383671
		Major Axis	155.885-1939.9
		Minor Axis	125.862-1288.65

2.5. Scalp problem classification

The classification is the process of classifying by which variables are classified into their classes [38]. In classifying the type of scalp conditions, the Support Vector Machine (SVM) technique is implemented. The SVM is one of the most successful classifiers, which is used to analyse the data and finding data trends [34]. The data is classified according to the statistical pattern. The SVM is also known as a binary classifier, in which data is classified according to the hyperplane [27]. It supports classification and regression functions, and can handle several continuous and categorical variables [39]. The SVM demonstrated to be an extremely robust and effective categorization and regression algorithm [40]. The classification is expected to classify the type of scalp conditions that the image belongs to. The final result which is the type of scalp condition will be produced promptly.

2.6. Performance evaluation

The performance of the scalp condition classification is evaluated using a confusion matrix. It is carried out by comparing the results of the SVM classification with the actual type of scalp conditions known. A total of 120 scalp condition images, in which 40 images for each type of scalp condition were tested. The number of TRUE and FALSE resulting from the classification in the form of a confusion matrix is tabulated in Table 3.

Table 3. Proposed confusion matrix of SVM pre-trained classification

		SVM Pre-trained Classification Result		
		Alopecia Areata (AA)	Dandruff	Normal
Actual Scalp Condition	Alopecia Areata (AA)	40 (TRUE)	0	0
	Dandruff	0	32 (TRUE)	8 (FALSE)
	Normal	0	10 (FALSE)	30 (TRUE)

Subsequently, according on the confusion matrix obtained in Table 3, the pre-trained classification accuracy for each type of scalp condition is calculated using (1):

$$Accuracy = \frac{\sum TRUE\ classification}{\sum images}\ x\ 100\% \quad (1)$$

3. RESULTS AND ANALYSIS

Hundred and twenty testing images are tested for each type of scalp conditions. The performance of the scalp condition classification is demonstrated in Table 4. From the accuracy measurement in Table 4, it is observed that the scalp condition classification produced an excellent classification for AA, which indicates 100% correct classification. The classification of dandruff and normal scalp returned good classification performance as well. The dandruff is observed to return 80% of accuracy, whereas the normal scalp scalp produced 75% of accuracy. The reasonably low percentage of accuracy for dandruff and normal scalp could be caused by the similar representations between these two scalp conditions. Yet, the overall mean percentage of accuracy which is 85% signifies a good classification outcome of the pre-trained classification of scalp conditions as a whole.

Table 4. Classification results

Scalp Condition	Total Image	TRUE Classification	% Accuracy
Alopecia Areata (AA)	40	40	100
Dandruff	40	32	80
Normal	40	30	75
		MEAN	85

4. CONCLUSION

This paper presented a study on pre-trained classification of scalp conditions using image processing techniques. The study is focusing on the three types of scalp conditions which are Alopecia Areata (AA), dandruff and normal. The three features of color, texture, and shape were extracted using feature extraction techniques in analyzing the characteristics of the scalp conditions. In another note, a Support Vector Machine (SVM) technique is used to classify the scalp conditions. The application has been successful for a variety of testing images. The performance of scalp conditions classification is evaluated using a confusion matrix. The overall mean percentage of accuracy demonstrated a very strong accuracy which is 85%. It can be inferred that the proposed pre-trained classification of scalp conditions using image processing techniques is found to be successful. However, it is recommended that the latest feature extraction and recognition techniques such as deep convolutionary neural network be introduced and integrated in the future.

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