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Extracting Novel Features for Skin Burn Image Classification

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***Abstract**: In this paper, the objective is to propose a set of novel features for the classification of different burn depths by using an image mining approach. Both colour and texture features were studied on skin burn dataset comprising skin burn images categorized into three burn depths by the burn specialist. The performance of the proposed feature set was evaluated using linear SVM on 10-fold cross validation method. The empirical results showed that the six proposed novel features, when used together with the common image features, was the best set of features that was able to classify most of the burn depths in terms of accuracy, precision and recall measures with the values of 96.8750%, 96.9697% and 96.6667% respectively. Automated classification of skin burn depths is essential because the initial burn treatment provided to patients are usually based on the first evaluation of the skin burn injuries by determining the burn depths. However, the burn specialist may not always be available at the accident site. In conclusion, the features extracted that represent the burn characteristics specifically in terms of colour and texture were able to effectively characterise the depth of burns in accordance to burn depth classification.*

***Keywords** : Burn Image Classification, Colour, Feature Extraction, Skin Burn Depths, Texture.*

I. INTRODUCTION

Burn accident is quite a common occurrence. It can occur to anyone, anywhere and at any time without any prior notification. Burns involving human skin can present serious issues if proper medical treatment is not given earlier on. It will lead to other complications or in more severe cases, it can be fatal.

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Human skin is made up of three layers as shown in Figure 1, which are: (i) the epidermis, the outermost layer of the skin, (ii) the dermis, laying underneath the epidermis and can be divided into two sub-layers, which are the papillary

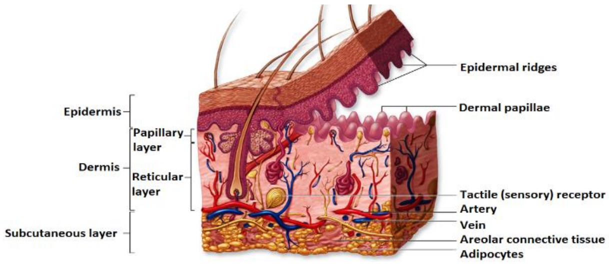

Fig. 1. Human skin structure [19]

layer (superficial) and reticular layer (deep) and (iii) subcutaneous layer, which is the inner layer comprises of fat and connective tissues [1]. Generally, burns are classified into: (i) Superficial burn, which involves only the epidermis, (ii) Partial thickness burn, which is further divided into (a) Superficial partial thickness burn, which involves the entire epidermis and the upper layer of the dermis (papillary layer) and (b) Deep partial thickness burn, which affects the entire epidermis and most of the dermis and (iii) Full thickness burn, in which all the layers of the skin are destroyed and may extend into muscle and bone [2].

Patients with burn injuries often consult doctors for treatment. The severity is determined by the depth of the burn, which is diagnosed by clinical visual examination. Occasionally the depth of the burn cannot be easily defined through visual examination, as there could be mixed depth appearance. Even an experienced burn specialist can sometime make mistakes on their evaluation of skin burn depths and hence the severity of the burns are misdiagnosed. Medical practitioners with limited experience may at times become confused with the various depth and severity of the burns, especially in complicated cases. In some rural areas, patients may only have access to Medical Assistant or Nurse-led healthcare facilities. Experienced burn specialists have an accuracy of 64% to 76% while inexperienced doctors have an accuracy of 50% in their diagnosis of burn depths [3]. In spite of that, evaluation by the burn specialist remained the most reliable and was the standard in determining burn depths [4]. The first assessment of the burn depths is important as a wrong assessment can result in inappropriate and inaccurate initial management of the burn injuries.

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These mistakes will eventually translates into poor healing process, infections, undesirable scars and impaired body functions post burns.

This work is motivated by the need for an effective automated skin burn depth classification as burn specialists and medical personnel are not always available on site during burn accidents. The current state-of-the-art in burn depth classification is performed by using deep learned convolutional neural network to identify features that are capable to differentiate between healthy skin and burn area [5]. The images used were captured using colour-thermal camera instead of digital camera and the images were manually registered with infrared markings. The colour-thermal camera is expensive to acquire as compared to the regular digital camera.

Besides that, there were two related works focusing on classifying burn images into two types of burns (burn that needed grafts and burns that did not need grafts) [6], [7] and three types of burns depths (superficial dermal, deep dermal and full thickness) [6]. They conducted experiments to translate the physical features that were unconsciously observed by experts when diagnosing a burn into mathematical features. The identified mathematical features later underwent feature selection to select features that best estimates the burn depths using Support Vector Machine (SVM). Accuracies of 66.2% and 83.8% were achieved using SVM when classifying burn images into three types of burn depths and two types of burns respectively [6]. In another research work, an accuracy of 79.73% was achieved using SVM for classification of burn images into two types of burns [7].

Another related work presented the classification of burn images into its burn depths using various classification techniques for comparison [8]. The classification techniques used were Template Matching (TM), K-nearest neighbour classifier (KNN) and SVM. These classifiers were trained using pre-labelled images before tested on new or unseen images. The accuracies of 66%, 75% and 90% were reported using TM, KNN and SVM respectively.

Automated classification of skin burn depth by using computer vision is still a challenging task especially when the digital images of various burn depths are captured under uncontrolled environment with various lighting and different camera resolution level used. In this paper, an image mining approach is used to evaluate the image of the skin burn injury and to classify its depth. Most of the classification of skin burn depths in previous research works tend to use the global feature extraction approach. Most of them used the colour feature as the main characteristic to differentiate between different burn depths. There were some related work focusing on extracting both colour and texture features [6], [7], [9]–[11]. Their extracted colour features were mostly statistical moment of common colour features such as variance of hue, mean of h-space, mean of lightness and so on. Texture features extracted were mostly skewness and kurtosis as well as contrast and homogeneity. Colour and texture are the characteristics observed by experts in order to differentiate the burn depths and give diagnosis [12]. Thus, in this research work, both colour and texture features are extracted to classify the burn depths. The main contribution of this paper is the finding of new features that are able to capture the knowledge of the burn specialist to characterize each burn depth for the classification of skin burn depths.

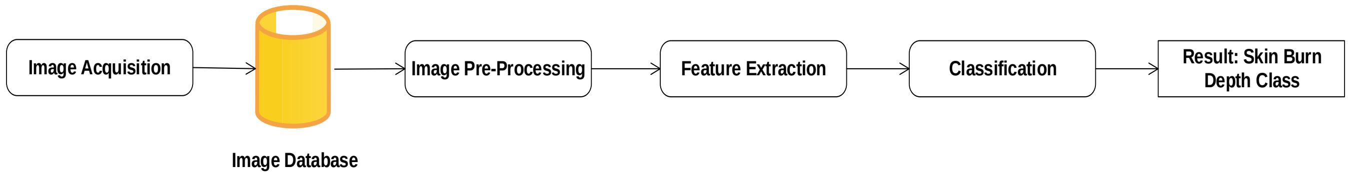

Fig. 2. Image mining approach

II. MATERIALS AND METHODS

This work proposes to use an image mining approach to evaluate the image of a skin burn injury and classify the burn injury into one of the burn depths. Image mining is not just an extension of data mining to image domain. It is an interdisciplinary field with a combination of techniques such as computer vision, image processing, image retrieval, data mining, machine learning, database and artificial intelligence [13]. Figure 2 shows the image mining approach that is used in this work. The image mining approach consists of several processes as described in the following sub-sections.

A. Image Acquisition

The burn images used in this work were collected by a burn specialist. There were no conditions for lighting or environment applied when the burn images were taken. There are currently no open source dataset available for skin burn depth. The skin burn depths considered in this work are second degree burn and third degree burn, specifically superficial partial thickness burn (SPTB), deep partial thickness burn (DPTB) and full thickness burn (FTB). The number of images collected for SPTB, DPTB and FTB were 24, 20 and 20 respectively with a total of 64 images.

B. Image Pre-Processing

All the collected images underwent pre-processing to eliminate images that did not show clear burn wounds, as they were affected by lighting. The images were then cropped to eliminate complex background. Besides that, the collected images were standardized to PNG format because preliminary experiments indicated that better results could be obtained.

C. Feature Extraction

Both colour and texture features were extracted in this work as both of them are significant in skin burn image analysis. There were several processes undertaken to extract colour and texture features from the skin burn images. These processes were used to extract three feature sets, namely Feature Set 1 (global features), Feature Set 2 (blister features) and Feature Set 3 (novel features).

C.1 Feature Set 1 – Global Features

This set of features were global feature and were extracted in term of statistical measures. Global features describe the image as a whole by generalizing the entire image with a single vector [14]. The global features produce very compact representation of an image but are very sensitive to clutter and occlusion in which a good segmentation of an object from the background image is assumed to be available. The extracted global features were the standard deviation of hue (*stdHue*), mean of a* channel (*meanA*), mean of b* channel (*meanB*), standard deviation of a* channel (*stdA*), skewness of a* channel (*skewA*) and kurtosis of a* channel (*kurtA*). Skewness and kurtosis are used to indicate burn that is moist and has bright colour [12]. This set of features was used to represent the colour characteristic of each burn depth generally from the generalized pixels of the whole image.

C.2 Feature Set 2 – Blister Feature Set

Blisters normally occur in SPTB while DPTB and FTB do not have blister. The blister is normally brownish in colour. The texture of SPTB is normally with moisture and looks wet as compared to DPTB and FTB. Before extracting the colour and texture features of the blister, the region that might consist of blister needs to be detected and segmented out from an image using the Otsu's method. The inverse of the binary image from the thresholding contain the blister. The morphological open with the specified structuring element is used. The specified structuring element used is a disk-shaped structuring element, with a radius of 5. Those pixels included in the morphological computation are true pixel, whereas those pixels that not included are false pixels. After that, the binary image is again dilated with disk-shaped structuring element, with a radius of 10. The dilated binary image is then performed using flood-fill operation to fill the holes in between the true pixels.

Grey intensity image is used to find the region that may contain blister, in which blisters appear as darker grey intensity pixels after contrast enhancement. However, there are some exception to the segmented darker grey intensity pixels to be considered as blisters. These are some darker grey intensity pixels that appear as a burn wound inside another burn wound or burn wound with low light intensity. To tackle this problem, the segmented regions with blisters and non-blisters are compared by extracting both colour and texture features. For SPTB, when there is no blister or non-obvious kind of blister exist, the colour and texture features of SPTB are extracted to compare with the colour and texture features of DPTB and FTB. The colour features that are extracted are the mean of chroma (*meanChromaBlister*) and the standard deviation of hue (*stdHueBlister*).

To measure the texture, texture analysis functions, standard deviation filter and entropy filter are used. Texture analysis tends to describe the spatial variation in pixel intensities, in terms of roughness, smoothness, silkiness or bumpiness of a region. In the output image, brighter pixels correspond to their neighbourhood, have larger standard deviations and higher entropy values. Therefore, the mean of standard deviation filter (*meanStdFiltBlister*) and the mean of entropy filter (*meanEntropyFiltBlister*) are extracted.

Grey-level co-occurrence matrix (GLCM) [15], is also used to examine the texture of the segmented region. There are four statistical properties that can be extracted from the GLCM, which are contrast, correlation, energy and homogeneity. In this work, the statistical properties extracted from GLCM are contrast and energy. Correlation and homogeneity are not used in this work because both of these values do not help in separating the different burn depths. Contrast measures the local variations whereas energy measures the uniformity in the matrix. The formulas for contrast and energy are shows in (1) and (2) respectively.

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \tag{1}$$

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

where, p(i, j) is the grey-level co-occurrence matrix in GLCM

The overall features that have extracted to compare SPTB with DPTB and FTB were mean of chroma (*meanChromaBlister*), standard deviation of hue (*stdHueBlister*), mean of standard deviation filter (*meanStdFiltBlister*), mean of entropy filter (*meanEntropyFiltBlister*), contrast (*contrastBlister*) and energy (*energyBlister*). This set of features has used to represent the blister of SPTB or texture of SPTB against the texture of DPTB and FTB.

C.3 Feature Set 3 – Novel Feature Set

The approach to extract novel features consists of four processes as described here.

<u>Process 1</u>

For the novel colour features extraction, the first process is to calculate the average and standard deviation colour ranges of the training image dataset. The histogram of the image in L*, a* and b* channels are partitions into bins and the bins are sorts with the specified bin edges. The specified bin edges for L* channel is 0 to 100 and for a* and b* channels are -26 to 100. The a* and b* channels include values from -26 due to the reason that beyond -26, the colour pixels tend to become more green and blue. The green and blue colours are not important in determining the burn depths. The count in each bin are then normalized with the total pixels of an image as shown in (3).

$$\text{NormalizedCount} = \frac{\text{countL}}{\text{totalPixels}} \times 100 \tag{3}$$

The normalization is done separately for L*, a* and b* channels for DPTB, FTB and SPTB. The normalized count are considered only for values more than or equal to 1.0. After that, the first bin and last bin values are obtained for DPTB, FTB and SPTB images respectively. The average minimum and maximum values of the normalized L*, a* and b* channels for DPTB, FTB and SPTB are calculated using the formulas as shown in (4) and (5) respectively.

$$AverageNormMin = \frac{\sum firstNormalized}{totalImages} \quad (4)$$

$$AverageNormMax = \frac{\sum lastNormalized}{totalImages} \quad (5)$$

where, *totalImages* = number of images in each burn depth

The minimum and maximum standard deviation of the normalized L*, a* and b* channels for DPTB, FTB and SPTB are calculated using the formulas as shown in (6) and (8) with the (7) and (9) showing the formula used in (6) and (8) respectively.

$$StdNormMin = \sqrt{\frac{\sum(firstNormalized - meanfirstNomalized)^2}{totalImages - 1}} \quad (6)$$

where,

$$meanfirstNormalized = \frac{(\sum firstNormalized)^2}{totalImages} \quad (7)$$

$$StdNormMax = \sqrt{\frac{\sum(lastNormalized - meanlastNomalized)^2}{totalImages - 1}} \quad (8)$$

where,

$$meanlastNormalized = \frac{(\sum lastNormalized)^2}{totalImages} \quad (9)$$

where, *totalImages* = number of images in each burn depth

Process 2

The second process for novel colour feature extraction is by using the pattern search algorithm to find the optimum weightage for the standard deviation colour ranges, which are computed from the training image dataset. This is due to the reason that average colour ranges from the training image dataset is not sufficient to represent some of the burn depths in term of colour pixels. Pattern search algorithm is one of the direct search method algorithm. Direct search solves optimization problem from a set of points around the current point without requiring any information of the higher derivatives. In this work, pattern search algorithm was used to find the maximum classification accuracy of the mean colour features (*meanDeepRange*, *meanSuperficialRange*, *meanFullRange*) that was possible to be achieved when adding the optimum weightage to the standard deviation colour ranges. This, in turn, is added to the average colour ranges obtained from the training image dataset.

This process allows different optimum weightage to be computed. This process is able to perform well even with different training image dataset used. The pattern search algorithm used is bound constraints, which means there are lower and upper bound limit to the components of the solution. The lower bound are set to 0 and upper bound are set to 2. The pattern search algorithm begins at the initial point, x_0 = 0. The 10-fold cross validation method and quadratic Support Vector Machine with one versus all classes approach are used to find the highest classification accuracy possible to be achieved. The features extracted by using the first and second processes were the mean of DPTB range (*meanDeepRange*), mean of SPTB range (*meanSuperficialRange*) and mean of FTB range (*meanFullRange*).

Process 3

The third process is to refine the colour range obtained from the training image dataset. Some of the colour pixels for example, white colour pixels for DPTB do not fall in the colour ranges obtained from the average and standard deviation of the DPTB training images. The white colour pixels that are supposed to be extracted as the colour characteristic for DPTB are not being covered in the range. Hence, the colour pixels from the training images are refined so that the colour characteristics that are important to each burn depth are covered. There are methods used in refining the colour ranges, which are the colour thresholder application implemented in MATLAB and the use of CIE L*a*b* colour chart as a guideline. There are a total of seven colour ranges used to define the burn depths, which are white, pink, dark red, light brown, dark brown, grey-white and beige-yellow. The colour ranges refer to the minimum and maximum values for L*, a* and b* channels. After setting the minimum and maximum value for channels L*, a* and b*, the colour ranges are used to threshold the L*a*b* image, in which pixels that fall into the colour ranges are the colour pixels that are important in representing the burn colour characteristics. After that, delta E (ΔE) is computed for each of the seven colours considered and was threshold with its mean to find the closest matching colour pixels.

Process 4

The fourth process is to calculate the percentage area of the colour of each burn depth in an image. The conditions applied to find the percentage area of the burn colour are as followed:

Condition 1 → Percentage colour area of FTB > Percentage colour area of DPTB AND Percentage colour area of FTB > Percentage colour area of SPTB

Condition 2 → Percentage colour area of FTB > Percentage colour area of DPTB / 2 AND Percentage colour area of FTB > Percentage colour area of SPTB / 2

Condition 3 → Percentage colour area of DPTB burn > Percentage colour area of SPTB

Condition 4 → Percentage colour area of DPTB burn > Percentage colour area of SPTB burn * 0.2

FTB is set to be in first condition because it is the most serious burn injury when compared with DPTB and SPTB.

Condition 1 and condition 2 are set to find the FTB colour area whereas condition 3 and condition 4 are set to find the DPTB colour area. If both conditions 1 and 2 are not fulfilled, the burn is not a FTB. The conditions 3 and 4 are to check whether the burn is a DPTB. If both conditions 3 and 4 are again not fulfilled, the burn is consider as SPTB. The features extracted by using third and fourth processes were percentage colour area of FTB *(isFull)*, percentage colour area of DPTB *(isDeep)* and percentage colour area of SPTB *(isSuperficial)*. *isFull* variable holds the percentage colour area of the FTB, *isDeep* variable holds the percentage colour area of the DPTB and *isSuperficial* variable holds the percentage colour area of the SPTB. This process was implemented to overcome the issues of a mixed burn depth appearance image that consisted of multiple colours of different burn depths and the colour that was significant to the burn depth appeared to have a small surface area compared to the colours that were non-significant to that particular burn depth, which occupied a larger surface area in the image.

The overall novel colour features that were extracted were mean of DPTB range (*meanDeepRange*), mean of SPTB range (*meanSuperficialRange*), mean of FTB range (*meanFullRange*), percentage colour area of FTB (*isFull*), percentage colour area of DPTB *(isDeep)* and percentage colour area of SPTB *(isSuperficial)*. This set of features is used to represent the colour characteristic of each burn depth as observed by the burn specialist when diagnosing a burn.

D. Burn Depth Classification

All the skin burn images used in this work for the training phase were pre-labelled by a burn specialist. Classification of the skin burn images was carried out using the multiclass classification approach. The classification algorithm used on the skin burn dataset was the linear SVM using the 10-fold cross validation method. The 10-fold cross validation method takes the average of the different test partitions in the dataset. Hence, the results would be void of bias. The metrics used to evaluate the performance of the classifier were accuracy, precision and recall.

III. RESULTS AND DISCUSSION

The feature set that was proposed in this work was compared with the feature set proposed by the previous research works as shown in Table 1. The overall performances for linear SVM on these feature sets are shown in Table 2. The proposed feature set is a combination of Feature Set 1, 2 and 3 from Section 2.3.

Table- I: Details for Feature Sets

Set ID	Features Proposed By	Feature Set
1	Proposed Feature Set	*meanDeepRange, meanSuperficialRange, meanFullRange, isFullBurn, isDeepBurn, isSuperficialBurn, stdHue, meanA, meanB, stdA, skewA, kurtA, meanChromaBlister, stdHueBlister, meanEntropyFiltBlister, meanStdFiltBlister, contrastBlister, energyBlister*
2	[6]	*chroma (C*a*b*), variance of hue (Vh*) and skewness of b* (skb*)*
3	[7]	*chroma (C*a*b*), hue (h), kurtosis of a* (ka*) and skewness of b* (skb*)*
4	[8]	*Mean and (2, 1)* th *coefficient of Discrete Cosine Transform (DCT) function of V1 chrominance of the L*a*b**
5	[10], [11], [16]–[18]	*MeanL, MeanHue, MeanChroma, StdL, StdHue, StdChroma, MeanA, MeanB, StdA, StdB, SkewL, KurtL, SkewA, KurtA, SkewB, KurtB*
6	[10], [11], [16]–[18]	*MeanL, MeanHue, StdHue, MeanA, StdB, SkewL*

Table- II: Classification Accuracy, Precision and Recall Values for the Compared Feature Sets by Using 10-Fold Cross Validation

Set ID	Accuracy	Precision	Recall
1	96.8750	96.9697	96.6667
2	70.3125	68.7784	68.8889
3	64.0625	64.1371	62.7778
4	64.0625	54.7174	62.2222
5	92.1875	92.2138	91.9444
6	78.1250	78.1062	77.5000

Based on Table 2, it can be seen that Feature Set ID 1, which is the proposed features in this work achieved the best performance with an average accuracy of 96.8750%, precision of 96.9697% and recall of 96.6667% as compared to Set ID 2, 3, 4, 5 and 6. Features from Set ID 3 and 4 had the poor performance compared to the others. On closer inspection, there are misclassification of image for the proposed features used in the work. Two FTB image were misclassified as DPTB. The *isFull* feature was able to get the percentage of the FTB area for both misclassified image. However, due to the reason that the two FTB image characteristic values were quite close to DPTB image characteristic values in terms of colour and texture, they were therefore misclassified.

IV. CONCLUSION

In conclusion, this research work was undertaken to extract novel features for the classification of skin burn images. The features were extracted based on colour and texture features. The proposed features in this work were compared with the features proposed by the previous research work on our collection of skin burn images. The performance of the proposed features was evaluated using linear SVM classification algorithm in terms of classification accuracy, precision and recall measures.

The best features set was the proposed features with an accuracy of 96.8750%, precision of 96.9697% and recall of 96.6667%. The classification of skin burn images is dependent on the features extracted, in which the features are able to represent the characteristics of a particular burn depth in the image. In future work, more colours can be studied to refine the colour ranges from the dataset so that the features extracted will be able to represent the colour of each burn depth more precisely and the accuracy of the classification of each burn depth can be improved.

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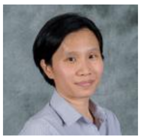

Dr Stephanie Chua serves as a Senior Lecturer in the Faculty of Computer Science and Information Technology (FCSIT), Universiti Malaysia Sarawak (UNIMAS). She obtained her Ph.D from the University of Liverpool, UK in 2012. Her research interests lie primarily in data, text and image mining. She is also interested in the areas of artificial intelligence and machine learning, applied data, text and image mining and exploratory data visualization and analysis. She has conducted research in text classification, text summarization, social media mining, frequent pattern analysis, sentiment analysis, genetic data mining, medical and epidemiological data analysis, medical image classification and other related application areas. She is also a Certified Data Science Specialist by iTrain Asia Pte Ltd. She is involved in various research projects in the areas of text mining and natural language processing. She also works closely with the colleagues from the Faculty of Medicine and Health Sciences (FMHS), UNIMAS in the development of clinic and health related application system and mobile application. In the last few years, she had participated in UNIMAS Innovation and Technology Exposition (InTEX) and had won a number of gold, silver and bronze medals for her project entries. She is currently a member of the International Association of Engineers (IAENG).

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Dr. William HC Tiong, a graduate from the National University of Ireland, Galway, was awarded his postgraduate Masters in Plastic, Reconstructive & Aesthetic Surgery qualification from Reconstructive Sciences Unit in Universiti Sains Malaysia. He also holds postgraduate qualifications from the Royal College of Surgeons in Ireland, and a higher education doctorate in Network of Excellence for Functional Biomaterials from Galway, Ireland. Over the years, he has a wealth of experience working in Plastic, Reconstructive, & Hand Surgery Centers as well as cosmetic surgery in hospitals in Ireland namely Cork University Hospital, University Hospitals Galway, and Connolly Hospital, Beaumont Hospital and Mater Misericordiae University Hospital in Dublin. In Temple St. Children's University Hospital in Dublin, Ireland, he gained wider exposure in the care of children with cleft lip and palate, and craniofacial deformities. In Malaysia, he has worked in Hospital Kuala Lumpur, Hospital Universiti Sains Malaysia, and Sarawak General Hospital, all of which are tertiary referral centers for burn care and leaders in reconstructive surgery in the field of head and neck cancers, breast cancers and limbs restoration. In addition, he is actively involved in propagation of knowledge through his involvement in lectures and seminars to medical students, and was invited as a speaker among professionals in Sarawak Oculoplastic Workshop. He has also presented in numerous conferences throughout in the world to share his ideas and knowledge in the field of restorative tissue engineering with fabricated collagen and in plastic surgery conferences. He is also a facilitator in Basic Surgical Skills Workshop under the Royal College of Surgeons in Ireland (RCSI) and Penang Medical College (PMC). Recently, he was also invited as a reviewer in peer-reviewed journal namely Journal of Plastic, Reconstructive & Aesthetic Surgery, British Journal of Pharmaceutical Research, British Journal of Medicine and Medical Research among others.

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