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A Robust Approach to Segment Human Skin and Burnt Region from Chaos Background Using Classification Trees

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Abstract - Accurate estimation of the total body surface area (TBSA) and its percentage is critical for efficient burn patient care. In this paper, we present a machine learning-based approach for segmenting burnt regions and healthy skin areas from the burn image dataset we collected, addressing challenges related to limited dataset size and chaotic hospital background. Our method utilizes a classification tree model trained on features extracted from the HSV color space, normalized RGB components, and Chroma values, then compare with ensemble trees (Random Forest and XGBoost). The results demonstrate robust performance in accurately segmenting burn regions and healthy skin, outperforming existing methodologies where reach 93.94% accuracy in healthy skin segmentation and 94.59% in burnt region segmentation. Additionally, we identify the need to augment the dataset with more diverse skin examples in future work to improve sensitivity in detecting healthy skin. Our approach provides a valuable contribution to the accurate determination of TBSA percentage, thereby streamlining the assessment and treatment process for burn patients.
***Keywords*:** burn care, image segmentation, machine learning, decision trees, classification trees

1. Introduction

The main cause of death for patients who get burned, accounting for 58% of fatalities within the first 72 hours, is the initial 'burn shock' which necessitates fluid resuscitation to support hemodynamics and perfuse end organs[1, 2]. The larger the burn, the more intense this process becomes. An accurate total body surface of a burn is acute in-patient care. At this time, given the lack of experience in burn injuries by most health care providers and first responders outside of the burn surgeon, inaccurate estimations lead to over-, under-, and unnecessary resuscitation of patients. Lack of training and experience has led to first responders giving an inaccurate estimation of the total body surface area (TBSA) and TBSA percentage[3].

To determine the TBSA and its percentage accurately and reduce the impact of chaotic background in the hospital when measuring the severity of burn injuries, separating the background, burned skin, and healthy skin region is essential. Machine learning methods are proven effective at image segmentation tasks. For instance, the deep learning-based end-to-end framework was applied to segment the burnt skin area in the whole images at reached the IOU of 0.8467 [4]. Cr-transformation, Luv-transformation, and fuzzy c-means clustering were used for segmenting the burnt region and discriminating between healthy skin and burned skin and obtained a sensitivity of 0.84 [5].

In this study, we gather a burn image dataset from a burn center and manually annotate healthy and burned skin at the pixel level. We select features such as HSV color space, normalized RGB components, and chroma values. Finally, we train a series of classification tree[6] including single tree, Random Forest [7] and XGBoost [8] with the extracted feature vectors to segment skin and burned regions, then evaluate and compare our models. Our proposed method successfully mitigates the constraints associated with limited dataset size and chaotic background conditions, culminating in strong performance metrics. This attests to the effectiveness of our approach in accurately segmenting burn-affected regions and distinguishing healthy skin areas.

2. Method

2.1. Data Collection

In this paper, the burn injury images were collected from 8 patients (6 males, 2 females) with varying ages (29-76 years old) and ethnicities (3 White, 5 Latinos) in collaboration with an expert at Texas Tech University Health and Science Center (TTUHSC), following IRB guidelines. The images captured burned body parts such as the face, feet, and abdomen of the patients on their first day of admission to the hospital. A total of 25 images were obtained, including 9 from patients with partial-thickness burns and 16 from patients with full-thickness burns.

2.2. Image Pre-processing

In the pre-processing stage, we manually label the original dataset at pixel level with 2 steps:

Step 1: We label the pixels belonging to healthy human skin for distinguishing from the background to obtain the total body surface area of the human and reduce the impact of chaotic background for further work. The original image is shown in Fig. 1a, and the labelled area is marked as the blue region shown in Fig. 1b.

Step 2: We label the pixels associated with burned area on patients' bodies for determining the TBSA, the labeled area is marked as the yellow region shown in Fig. 1b.

Prior to training the classification tree, we implement the Normalization-Contrast Limited Adaptive Histogram Equalization (N-CLAHE) [9] to minimize the effects of different qualities such as intensity and lightness of the original images. The image processed by N-CLAHE is shown in Fig. 1c.

(a) (b) (c)

Fig. 1: (a) Original image from burn patient. (b) Labelled image with total human skin area (healthy + burned). (c) Labelled image with the total burned skin area. (c) Pre-processed image after N-CLAHE algorithm

2.3. Feature Extraction

To determine which pixels are related to the human skin and burnt region, we select 8 color-related features which include pixel values on HSV (Hue, Saturation, and Value) color space, two components of the normalized RGB color space (r-g), and chroma values as shown in Eq. (1):

$$[pixel_H, pixel_S, picel_V, r, g, chroma] \tag{1}$$

where $pixel_H$, $pixel_S$, and $picel_V$ represent the pixel values in HSV color space [10] which is more focused on the nuances of how humans perceive color; r, g are the components of the normalized r-g color plane which has been proven effective to reduce the dependence of luminance and recognize different people's skin colors [11]. The normalized components are calculated by following Eqs. (2)-(3):

$$r = \frac{R}{R+B+G} \tag{2}$$

$$g = \frac{G}{R+B+G} \tag{3}$$

where R, G, B values are the pixel values at R, G, B channels of the images.

Chroma values are hired for determining if the pixel is in the burn region by colorfulness[12].

2.4. Model training

Classification tree is a type of decision trees which is a supervised learning algorithm for binary classification tasks [6]. The classification tree model is a hierarchical tree structure, wherein every decision node signifies a feature in our proposed feature vector, and every branch represents a decision rule founded on the value of the corresponding feature and terminates at a leaf node that corresponds to the class label. And the classification tree doesn't change to the input feature due to it doesn't consider multiple combined factors with varying importance at the same time [13]. We divided the dataset into 70% training set and 30% testing set randomly and trained the classification tree with training set and trained two different classification trees for burn region and healthy skin region separately. We applied the one-vs-all [14]method for each classification tree, for example, we treated the burn region as one class while merging the healthy skin and background regions as the other class for burn region segmentation, and vice versa for the healthy skin region classification.

In this paper, we also compare single classification tree with two commonly used ensemble tree-based techniques: Random Forest and XGBoost where Random Forest uses bagging to combine multiple decision trees to make predictions, while XGBoost applies gradient boosting to iteratively improve the model's performance. The number of trees is set to 50 for both algorithms in our experiments.

3. Result

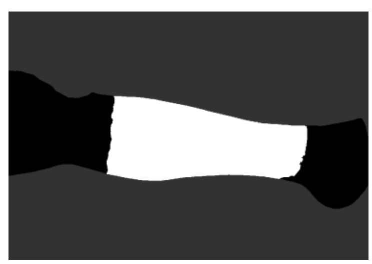
We evaluate our proposed method with performance metrics including 1) sensitivity, 2) specificity, 3) precision, 4) accuracy, 5) F-score, and 6) time consumption. In this paper, sensitivity assesses the ability of the model to correctly detect the positive regions (i.e., healthy skin or burnt skin) in a testing image, and specificity assesses how accurately the model identifies the negative regions (i.e., healthy skin region and background are negative regions for burnt region) in a testing image, precision evaluates the model's accuracy in identifying positive regions and reducing falsely identifying negative regions as positive, accuracy measures the overall correctness of the model, F-score is a composite metric that combines both precision and sensitivity used for evaluating the overall performance of the model, and time consumption measures the time costing during training phase. These performance metrics are shown in Table 1:

Table 1: Performance metrics of decision trees when segmenting healthy skin and burnt region.

Algorithm	Recognized region	Sensitivity	Specificity	Precision	Accuracy	F-score	Training time consumption
Classification tree	Healthy skin region	76.33%	96.94%	80.95%	93.94%	78.57%	186.78s
	Burnt region	91.44%	96.03%	91.28%	94.59%	96.07%	258.00s
Random forest	Healthy skin region	72.09%	96.44%	77.50%	92.90%	74.70%	6433.23
	Burnt region	89.24%	95.34%	89.69%	93.44%	89.47%	6259.90s
XGBoost	Healthy skin region	72.76%	96.87%	79.83%	93.36%	76.13%	127.67s
	Burnt region	90.38%	95.64%	90.39%	94.00%	90.39%	125.43s

After testing our trained model with the testing set, we present the single classification tree results of our predictions in Fig. 2. Specifically, Fig. 2a presents the original images from the testing set; Fig. 2b exhibits the ground truth mask which is generated from labels where the white section represents burnt region, black section represents healthy skin region, and grey section represents background; Fig. 2c demonstrates the recognition result of healthy skin region; and Fig. 2d illustrates the recognition result of the burnt region.

(a)



(b)

(c)

(d)

Fig. 2: Prediction results of our proposed method. (a) Original image from testing set. (b) The ground truth mask generated from labels (white: burnt region, black: healthy skin, grey: background). (c) Predicted result of healthy skin region. (c) Predicted result of burnt region.

4. Discussion

From Table 1, it is evident that our proposed method effectively addresses the constraints imposed by limited dataset size and chaotic backgrounds, ultimately achieving commendable performance metrics in the process. It outperforms the approaches described in [4] and [5], indicating a superior ability to discern burn-affected skin within the provided images where the models achieve the least accuracies of 92.90% on healthy skin region segmentation and 93.44% on burnt region segmentation. However, it is worth noting that the compared ensemble methods, Random Forest and XGBoost, have higher complexity and may not always be necessary for relatively simple datasets or features like the one used in this study. Traditional classification trees may be sufficient and more straightforward in such cases. Surprisingly, XGBoost shows higher efficiency during training by training 50 trees in the shortest time compared to the other models. A fly in the ointment is it exhibits a lower sensitivity in comparison to specificity when detecting healthy skin. This discrepancy may be attributed to an insufficient representation of diverse human skin tones within the dataset. In our future work, we will augment the dataset by incorporating a more comprehensive array of skin examples, thereby ensuring a more balanced performance in accurately detecting both background and skin regions, and transition to take whole-body pictures for estimation of the total body surface area.

By observing Fig. 2c and 2d, and the annotated mask presented in Fig. 2b, we found that the classification trees are adept at accurately identifying and eliminating the intricate and disorderly background in the hospital environment. Furthermore, Fig. 2d demonstrates the efficacy of our proposed methodology in segmenting the burn region from the patient's body, which can subsequently be utilized for the assessment of the Total Body Surface Area (TBSA). By determining the TBSA in conjunction with the healthy skin region, it is possible to facilitate a more streamlined calculation of the TBSA percentage.

References

[1] K. J. Zuo, A. Medina, and E. E. Tredget, "Important developments in burn care," *Plastic and reconstructive surgery*, vol. 139, no. 1, pp. 120e-138e, 2017.

[2] T. J. Schaefer and O. N. Lopez, "Burn resuscitation and management," in StatPearls [Internet]: *StatPearls Publishing*, 2022.

[3] Q. E. Chan, F. Barzi, L. Cheney, J. G. Harvey, and A. J. Holland, "Burn size estimation in children: still a problem," *Emergency Medicine Australasia*, vol. 24, no. 2, pp. 181-186, 2012.

[4] H. Liu, K. Yue, S. Cheng, W. Li, and Z. Fu, "A framework for automatic burn image segmentation and burn depth diagnosis using deep learning," *Computational and Mathematical Methods in Medicine*, vol. 2021, 2021.

[5] K. Wantanajittikul, S. Auephanwiriyakul, N. Theera-Umpon, and T. Koanantakool, "Automatic segmentation and degree identification in burn color images," in *The 4th 2011 Biomedical Engineering International Conference*, 2012: IEEE, pp. 169-173.

[6] L. Breiman, Classification and regression trees. *Routledge*, 2017.

[7] L. Breiman, "Random forests," *Machine learning*, vol. 45, pp. 5-32, 2001.

[8] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 2016, pp. 785-794.

[9] K. Koonsanit, S. Thongvigitmanee, N. Pongnapang, and P. Thajchayapong, "Image enhancement on digital x-ray images using N-CLAHE," in 2017 10th *Biomedical engineering international conference (BMEICON*), 2017: IEEE, pp. 1-4.

[10] K. Sobottka and I. Pitas, "Face localization and facial feature extraction based on shape and color information," in Proceedings of *3rd IEEE international conference on image processing*, 1996, vol. 3: IEEE, pp. 483-486.

[11] J.-G. Wang and E. Sung, "Frontal-view face detection and facial feature extraction using color and morphological operations," *Pattern recognition letters*, vol. 20, no. 10, pp. 1053-1068, 1999.

[12] D. Yadav, A. Sharma, M. Singh, and A. Goyal, "Feature extraction based machine learning for human burn diagnosis from burn images," *IEEE journal of translational engineering in health and medicine*, vol. 7, pp. 1-7, 2019.

[13] C. Kingsford and S. L. Salzberg, "What are decision trees?," Nature biotechnology, vol. 26, no. 9, pp. 1011-1013, 2008.

[14] R. Rifkin and A. Klautau, "In defense of one-vs-all classification," *The Journal of Machine Learning Research*, vol. 5, pp. 101-141, 2004.