Color Space Assessment for Automatic Chronic Wound Segmentation

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***Abstract*— Chronic wound diagnosis using machine learning is hindered by the lighting and shadows in the captured images. Therefore, this study evaluates the impact of different color spaces on wound segmentation using a U-Net. Results show that the YDbDr color space outperforms RGB.**

I. Introduction

The healing status of a wound depends on changes in the wound area. Therefore, an accurate and prompt assessment is essential—this is where Chronic Wound Segmentation (CWS) using machine learning can play a significant role [1]. Most current datasets consist of images acquired with digital cameras without a standardized protocol, which leads to issues with model robustness due to lighting conditions. To a computer, images are simply numbers, whose colors can be represented in different ways, i.e. Color Spaces (CS). This CS can mitigate the influence of shadows [2]. For this reason, [3] proposed the use of different CS in the CIFAR-10 dataset to analyze the effects on classification accuracy of everyday objects and animals. In this paper, we propose the use of different CS to compare the efficiency of CWS using a U-Net.

II. Materials & Methods

Initially, 188 images were selected from WoundsDB [4]. The first stage involved creating masks for the limb corresponding to the wound location to segment the images. The maximum dimensions of the bounding boxes were then determined using Ultralytics YOLO11 for object detection [5], then images were rescaled to the same dimensions as the maximum bounding box. To complete preprocessing, images were resized to 512×512 pixels and transformed into six CS: HSV, CIELab, RGB, YCbCr, YDbDr and CieLUV.

The next stage involved implementing transfer learning with a U-Net model using a VGG16 backbone, which was pre-trained on ImageNet [6]. Each model was subsequently retrained over 100 epochs with each CS using 80% of the images (150) for training (135) and validation (15), and 20% for testing (38 images). This resulted in six models, which were evaluated using the Intersection over Union (IoU), Dice Similarity Coefficient (DSC), precision, and recall metrics.

III. Results

The segmentation model's performance is presented in Table 1. YDbDr demonstrated the highest performance across most metrics, except for precision, where YCbCr performed better. The lowest was CIELab, with values up to 0.6944 for IoU and 0.8196 for DSC. These results reflect a difference of 0.08 (IoU) and 0.05 (DSC) compared to YDbDr. While the approach was different, [1] achieved an increase of +0.018 for IoU and +0.02 for DSC by merging channels from YCbCr and CIELab to segment chronic wounds. Unlike the results in [3], where CIELab showed a better classification performance, it proved to be the least effective in CWS, as seen in Figure 1.

Table 1. Performance Metrics of the Segmentation Model

Color Spaces	Metrics			
	IoU	***DSC***	***Precision***	***Recall***
HSV	0.7221	0.8386	0.9035	0.7825
CIELab	0.6944	0.8196	0.8428	0.7977
RGB	0.7618	0.8648	0.9106	0.8234
YCbCr	0.7266	0.8416	0.9212	0.7747
YDbDr	0.7752	0.8734	0.9092	0.8402
CieLUV	0.7354	0.8475	0.9034	0.7981

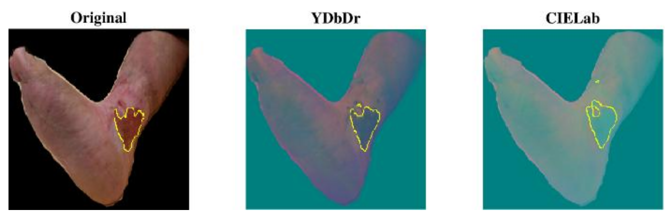

Figure 1. Results of CWS in CS: Original, YDbDr and CIELab.

IV. Conclusion

The analysis confirms that the use of CS like YDbDr can improve CWS performance, although the appropriate CS may vary in other applications. Additionally, these results could be affected by the transfer learning process. Therefore, although the findings are promising, further work is needed to address limitations not only in the amount of data but also in preprocessing, which is not yet fully automated, as well as to explore other CS like those presented in this paper.

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