The Edge of Healing: Interpreting Spatial Color Patterns in Complex Wounds

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INTRODUCTION

Combat-related extremity wounds often require repeated debridement surgeries and negative pressure wound therapy prior to delayed wound closure. Differences in light absorption between deoxyhemoglobin and oxyhemoglobin in wound beds produce colorimetric signals measurable as red, green, and blue (RGB) intensity profiles. Because healing progress may vary across the wound bed, we evaluated whether RGB features from wound margins versus the center better predict successful closure using image data.

METHODS

We reviewed 73 patients with 116 combat-related extremity wounds treated at Walter Reed National Military Medical Center during Operation Iraqi Freedom and Operation Enduring Freedom. RGB channel intensities and differences (*e.g.*, R–B, G–B) were extracted from 373 wound images using ImageJ software (Figure 1). Each image was normalized and segmented into 100 left-to-right percentile-based column profiles. A preliminary analysis was performed to evaluate five regions of the wound (region 1, 2, 3, 4, and 5), using Boruta feature selection, to identify RGB variables associated with successful closure (Figure 2). For model development, we classified the 100 left-to-right percentile-based column profiles as margin 1 (1–33), center (34–66), or margin 2 (67–100) (Figure 3A). Among 103 wounds with images obtained on the day closure was attempted, Boruta feature selection identified RGB variables associated with successful closure. Selected features were used to train XGBoost models to predict successful delayed wound closure. Model performance was assessed using area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and Brier score. Uncertainty was quantified with 95% confidence intervals (CI).

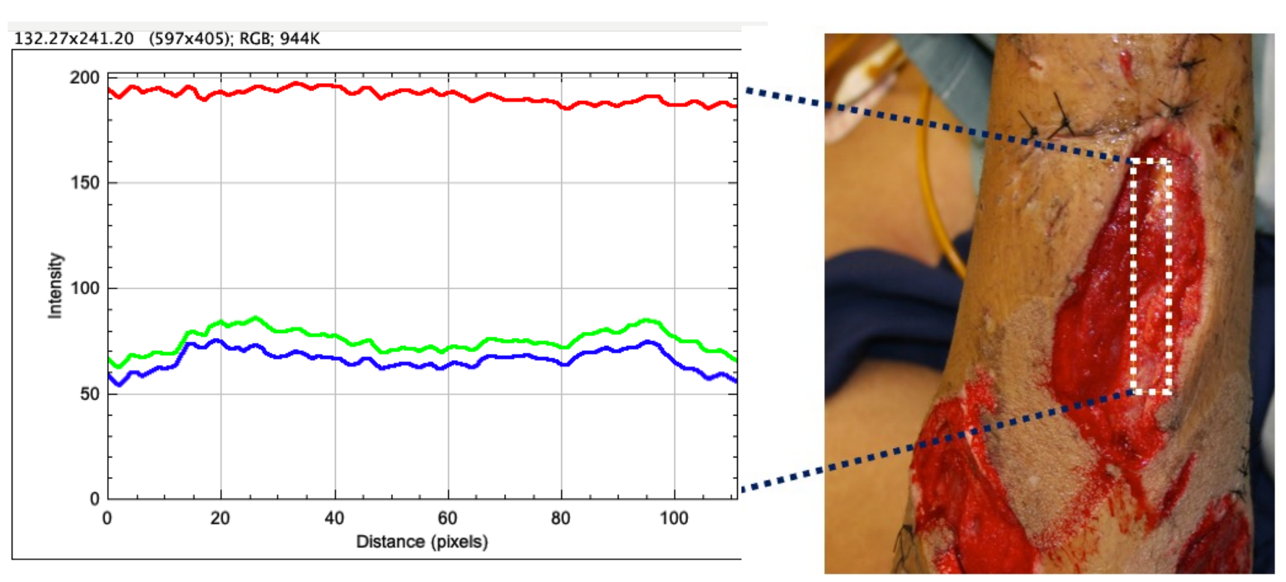

Figure 1. Extraction of RGB profile data from wound images. Wound images were analyzed in ImageJ, and each image was normalized and segmented into 100 left-to-right percentile-based column profiles spanning the wound from one margin to the opposite margin. For each column profile, pixel signal intensities from the red, green, and blue channels were extracted. The representative plot shows RGB channel intensities across the wound distance, which served as the basis for subsequent calculation of channel differences, including red minus blue (R–B), and for feature selection and model development.

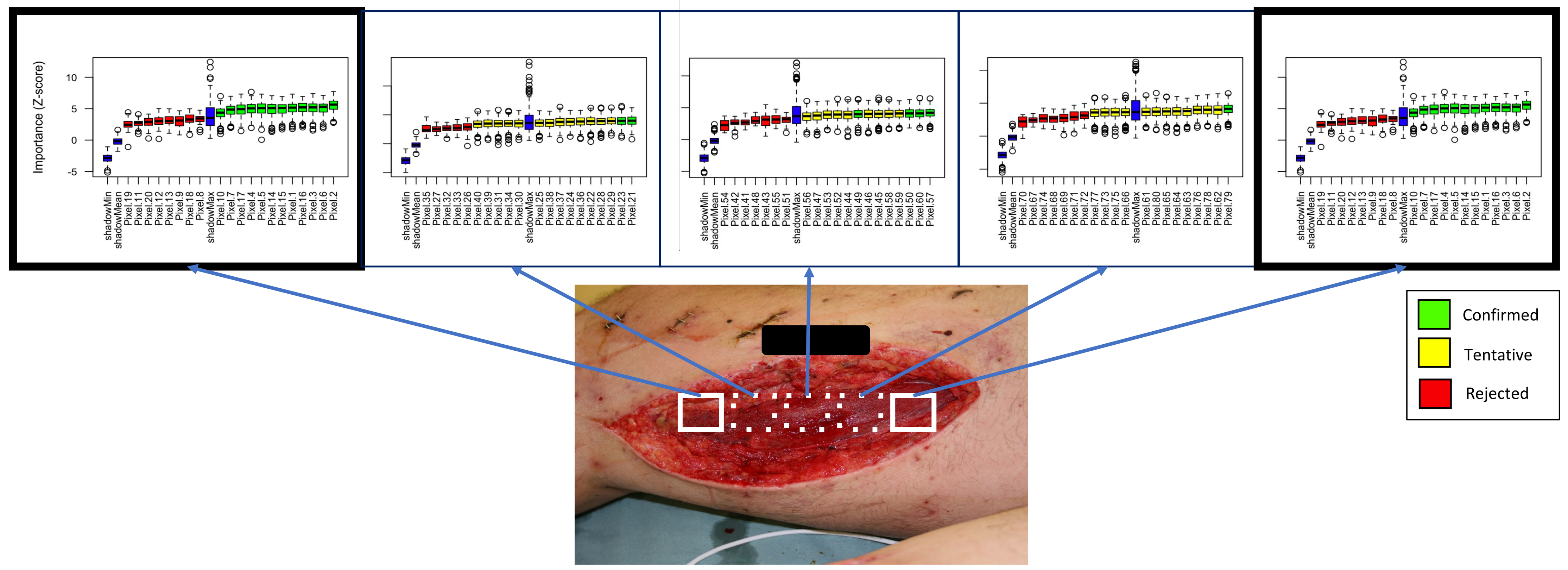

Figure 2. Primary evaluation of wound region. The Boruta algorithm was used to select variables based on RGB data from five wound regions indicated by the white boxes within the wound bed. The solid white boxes mark the wound margins, the regions where the most relevant variables were identified. For each region, the investigated variables were percentile-based column profiles derived from the RGB data. The box plots show Boruta importance Z-scores for these variables in relation to the prediction of successful delayed wound closure, alongside shadow variables generated by random permutation. Variables classified as highly relevant are shown in green, those with marginal relevance in yellow, and those with no relevance in red.

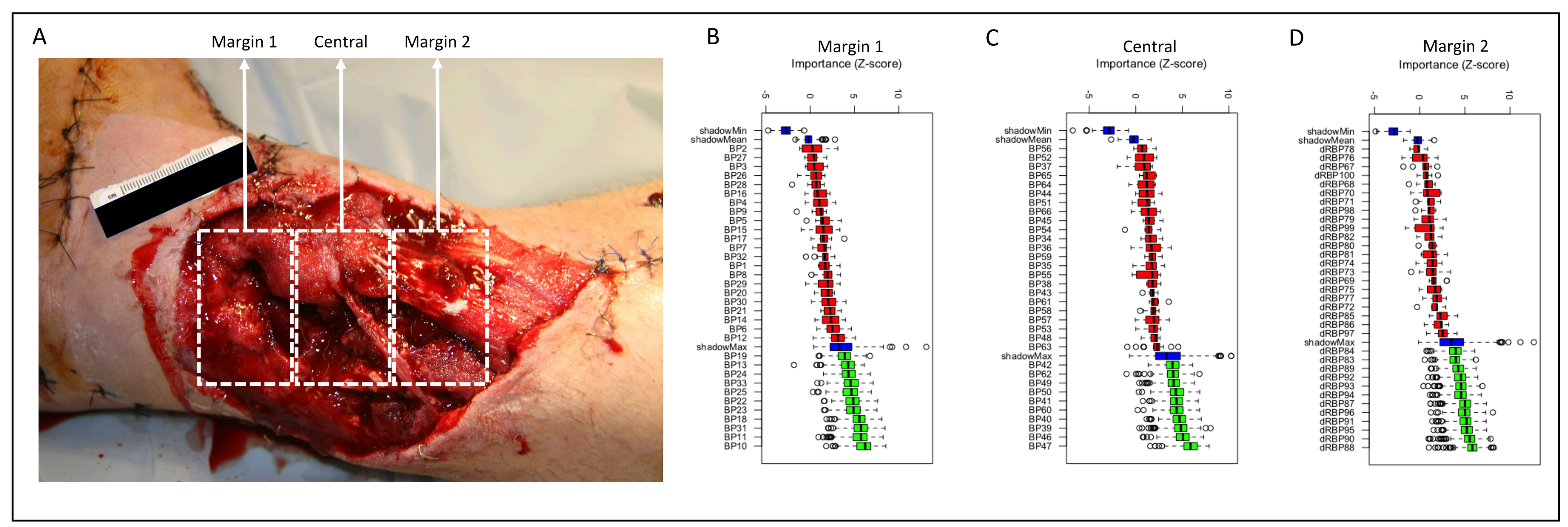

Figure 3. Image analysis for model development. Variable selection using the Boruta algorithm was based on RGB data from three wound regions (denoted by the white boxes in image A), using both the blue-channel column profiles (BP) and the difference between red- and blue-channel column profiles (dRBP). The wound image (A) was divided into 100 left-to-right percentile-based column profiles, which were evaluated separately as margin 1 (1–33), center (34–66), and margin 2 (67–100). Box plot (B) demonstrates Boruta importance Z-scores of BP variables in margin 1 for prediction of successful delayed wound closure. Relevant column percentiles identified in this region were BP10, BP11, BP31, BP18, BP23, BP22, BP25, BP33, BP24, BP13, and BP19 (N = 11). Box plot (C) demonstrates Boruta importance Z-scores for BP in the central wound region. Relevant column percentiles identified in this region were BP47, BP46, BP39, BP40, BP60, BP41, BP50, BP49, BP62, and BP42 (N = 10). Box plot (D) demonstrates Boruta importance Z-scores for dRBP in margin 2. Relevant column percentiles identified in this region were dRBP88, dRBP90, dRBP95, dRBP91, dRBP96, dRBP87, dRBP94, dRBP93, dRBP92, dRBP89, dRBP83, and dRBP84 (N = 12). dRBP was used for margin 2 instead of BP because this arrangement of variables was best for model development and performance.

RESULTS

The Boruta algorithm identified relevant variables in margin 1 (Figure 3B), the central wound area (Figure 3C), and margin 2 (Figure 3D). However, most of the relevant variables identified in the central wound area contributed little to model performance for predicting successful delayed closure (Figure 4). The top six blue-channel percentiles from margin 1 and the top six red-minus-blue (R–B) difference percentiles from margin 2 contributed most to model performance. A margin-only model incorporating these 12 variables achieved higher AUC, sensitivity, and specificity than a model that additionally included the selected central wound percentiles (N = 10) (Table 1). As a general principle, predictive model performance typically improves when more variables are added, indicating that the decrease in performance in the larger model here is likely due to collinearity between the two sets of data.

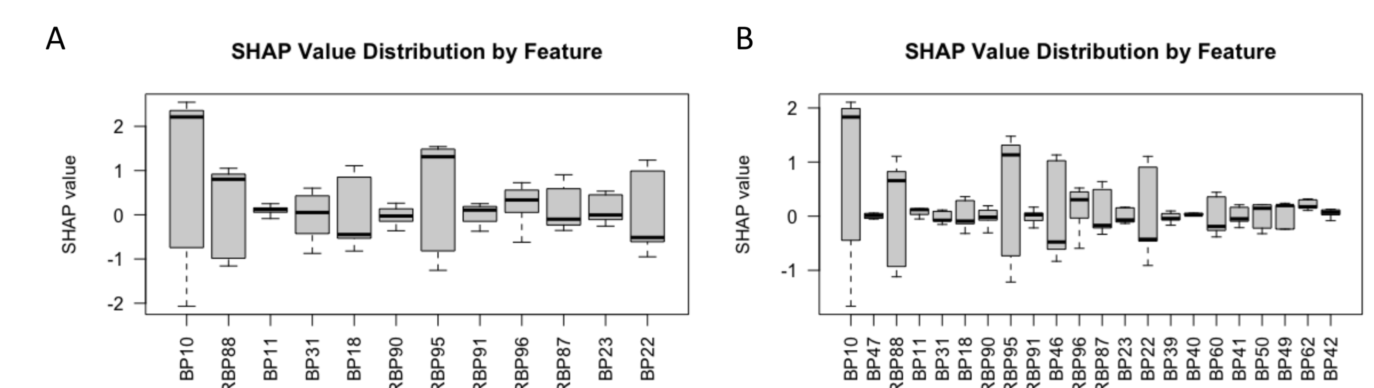

Figure 4. SHapley Additive exPlanations (SHAP) value distributions for features included in predictive models of successful delayed wound closure. **(A)** SHAP values for the best-performing model, based on the top selected column profiles from margin 1 (N = 6) and margin 2 (N = 6). **(B)** SHAP values for a model including all features from panel A plus all selected column percentiles from the central wound region (N = 10). Box plots show each feature's contribution to model output across observations; higher absolute SHAP values indicate greater influence on prediction.

Performance Metrics (95% CI)	Margin-Only Model	Model Including Margins and Central Percentiles
AUC	0.72 (0.69–0.74)	0.65 (0.62–0.67)
Sensitivity	0.71 (0.67–0.75)	0.65 (0.62–0.69)
Specificity	0.60 (0.58–0.62)	0.55 (0.53–0.57)
Brier Score	0.17 (0.16–0.18)	0.18 (0.17–0.19)

Table 1. Performance metrics of the XGBoost models. The margin-only model was developed using the top-performing BP percentiles from margin 1 (N=6) and dRBP percentiles from margin 2 (N=6). The second model was generated by adding selected central wound percentiles (N=10) to the margin-only model. Performance was assessed using area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and Brier score.

CONCLUSION

RGB features derived from wound margins were more informative than center-derived features at predicting successful delayed closure. These findings suggest that easily measured, spatially localized color patterns reflect the progress of complex healing processes that are difficult to quantify. External validation with independent data is required. Future studies should evaluate whether combining same-day clinical variables with image features improves predictive performance and clinical applicability.

*SC2i is a consortium of Walter Reed National Military Medical Center, Duke Health, Emory University School of Medicine, and Henry M. Jackson Foundation for the Advancement of Military Medicine, Inc.