Predicting Wound Healing with Machine Learning-Driven Digital Image Speckle Correlation

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BACKGROUND: Clinicians currently lack objective tools to predict when a wound will heal or whether healing is progressing appropriately, forcing reactive management that delays intervention and wastes critical treatment windows. Existing AI wound assessment technologies trained on image color features show reduced accuracy on darker skin tones (1), particularly because underserved populations bear a disproportionate chronic wound burden. We developed an AI-driven platform that predicts wound healing day from objective biomechanical data using digital image speckle correlation (DISC), with a detection pipeline that operates independently of skin pigmentation.

METHODS: DISC measures mechanical force propagation through healing tissue by tracking displacement of natural skin features under controlled point loading via video (2). We automated wound boundary detection using two zero-shot AI foundation models (Grounding DINO, SAM) that rely on gradient-based intensity patterns rather than learned color features, enabling detection across all skin tones without wound-specific training data. Using a 28-day porcine burn model (six treatment groups, two application timepoints), we trained eight machine learning architectures on five features: wound closure percentage, DISC-derived force propagation ratio, applied force, treatment type, and application timing (n=614, days 7 to 28, 10 repeated 80/20 train-test splits).

RESULTS: All eight models outperformed a baseline predictor (MAE 5.55 days). Performance was consistent across linear, tree-based, kernel, and ensemble methods, and within-7-day accuracy ranged from 85% to 91%, confirming that the predictive signal in DISC-derived features is model-agnostic. The best-performing model (KNN) achieved MAE of 3.39±0.25 days, R-squared of 0.549±0.051, and within-7-day accuracy of 90.6±2.6%. Accuracy at tighter prediction windows reached 47.5% within 3 days and 75.9% within 5 days. Feature importance analysis using iterative Random Forest (3) with stability analysis identified wound closure (48.4%) and force propagation ratio (17.6%) as the two dominant predictors, followed by treatment type (15.2%) and applied force (14.9%). Ablation confirmed that removing wound closure degraded MAE by 0.94 days, and that force propagation ratio adds predictive value beyond visual closure alone. Per-day prediction errors ranged from 2.4 days (day 21) to 4.6 days (day 28), with no systematic bias toward overprediction or underprediction.

CONCLUSIONS: This AI-driven predictive platform demonstrates that DISC biomechanical data contain sufficient information to predict healing day with approximately 90% accuracy within one week. Because the system detects tissue boundaries through mechanical displacement rather than color, it avoids known bias in medical imaging AI and provides equitable assessment across skin tones. These results support DISC as a clinical platform with applications in remote wound monitoring via telemedicine, burn zone prediction for surgical triage, debridement timing, and standardized assessment by non-specialist clinicians.

References:

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