# A Tale of Two Tissues: Machine Learning Classification of Cartilage Defect Preparation Depth Based on Debridement Audio Features Using a Novel Arthroscopic Microphone

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INTRODUCTION: Accurate preparation of the cartilage defect is a critically important step in joint preserving techniques such as matrix-induced autologous cartilage implantation. The goal of defect preparation is removal of all pathological cartilage without breaching beyond the calcified layer (CCL) into vascular subchondral bone. This task is technically demanding, leading to wide variability in surgeons' abilities to perform it accurately.[1] The sound of debridement can be used to perceive the preparation endpoint, owing to the differing sounds of cartilage and CCL debridement.[2] We previously developed a novel arthroscopic curette microphone to transmit these sounds during closed, arthroscopic cartilage defect preparation. In this study, we used audio features from cartilage and CCL debridements to train and validate four machine learning (ML) models to classify tissue depth during arthroscopic cartilage defect preparation.

METHODS: We used human osteochondral allograft remnant tissue (n = 4) to prepare 16 cartilage defects in the fashion used for MACI (8 to the deep cartilage, 8 to the CCL). Debridement audio was recorded using our novel arthroscopic microphone fixed to the back of a ringed curette. Each defect preparation depth was verified histologically. Curette strokes at each tissue layer were manually segmented and labelled as "Cartilage" or "CCL," then processed using a 0.1 to 20 kHz bandpass and preemphasis filters. Twenty-four audio features were extracted from a power-spectral density analysis of each curette stroke, including measures of loudness (i.e. root means squared amplitude), measures of frequency (i.e. centroid), and measures of spectral complexity (i.e. rugosity). The dataset was then split into a 75% training set and a 25% testing set using a grouped, stratified split to prevent data leakage. We used random forest recursive feature elimination with 10-fold cross validation to identify the most important audio features for model training. The resulting six audio features were used to train four models on the 75% training data set using 10-fold cross validation: logistic regression (LR), random forest (RF), XGBoost (XGB), and support vector machine (SVM). Each model was then tested using the held-out testing set. Models were evaluated using receiver operating curve area under the curve (AUC), overall accuracy, sensitivity and specificity for detecting the CCL, and F1 score.

RESULTS SECTION: There were 292 histology-verified curette strokes included in the data set (168 deep cartilage, 124 CCL). The six audio features identified as most important by recursive feature elimination were ratio-to-total-spectral-power in the 18.5-20 kHz band, peak amplitude, rugosity, decibel level, root means squared amplitude, and ratio-to-total-spectral-power in the 11-13 kHz band. All four models performed excellently on the classification task, with identical accuracies of 93%. The RF, XGB, and SVM models all had comparable AUCs of 0.98, with the LR model having a slightly lower AUC of 0.96. All models had a high sensitivity for detecting when the CCL had been reached (RF, XGB, and SVM 97%, LR 94%). In the XGB model, the ratio-to-total-spectral-power in the 18.5-20 kHz frequency band was the most important audio feature contributing to model performance (relative importance 0.34).

DISCUSSION: We found that four simple ML models are able to classify deep cartilage versus the CCL with near-perfect accuracy when trained on audio features from a novel curette microphone. The most important audio features for discriminating tissue type were high frequency bands (18.5-20 kHz, 11-13 kHz), loudness, and rugosity (the roughness of the amplitude signal). This supports previous descriptions of cartilage debridement being a rough, scratchy sound compared to the smooth gliding sound of debridement at the CCL.[2] This method for using debridement audio to classify debridement depth can be used to provide real-time feedback to users performing this task when using a curette equipped with piezoelectric sound transmission. More work is needed to determine how having real-time audio feedback and ML-based tissue classification assistance affects debridement accuracy. This study is limited by the cadaveric design that may differ from the interoperative setting MACI is performed in. Additionally, a single author that performed all debridements without a systematic control for debridement technique, which may differ between surgeons and affect model performance.

SIGNIFICANCE/CLINICAL RELEVANCE: A curette microphone may be implemented to restore audible feedback for cartilage defect preparation when done arthroscopically. These findings suggest that ML algorithms can be used to accurately classify tissue type based on audio features gathered with this microphone. Machine learning models such as these can be used to provide real-time feedback on debridement depth accuracy to surgeons. This ML-based feedback system may also be used in a cadaveric-training setting to help trainees more effectively acquire the challenging skill of cartilage defect preparation.

REFERENCES: 1. Yanke et al. 2019; 2. Hevesi et al. 2021.

**Table 1: Model performance comparison**

| Model | AUC (95% CI) | Accuracy | Sensitivity (TPR) | Specificity (TNR) | F1-Score |
|---|---|---|---|---|---|
| Logistic Regression | 0.96 (0.91-1.00) | 0.930 | 0.943 | 0.922 | 0.917 |
| Random Forest | 0.98 (0.97-1.00) | 0.930 | 0.971 | 0.902 | 0.919 |
| XGBoost | 0.98 (0.96-1.00) | 0.930 | 0.971 | 0.902 | 0.919 |
| SVM | 0.98 (0.95-1.00) | 0.930 | 0.971 | 0.902 | 0.919 |

*Sensitivity and specificity defined for detecting CCL

Figure 1: Model receiver operator characteristic plots