Deep Learning-Based Predictions of Polyethylene Insert Wear in Total Knee Replacements

Mattia Perrone[1], Scott Simmons[2], Steven P. Mell[1]

[1]Rush University Medical Center, Chicago, IL, [2]Drury University, Springfield, MO
Email of Presenting author: steven_mell@rush.edu

INTRODUCTION: Polyethylene wear remains a leading cause of long-term failure in total knee replacements (TKRs)[1]. Studies leveraging finite element analysis (FEA) models have shown that variability of gait patterns can lead to significant variability in wear rates[2]. However, FEA models can be resource-intensive and time-consuming to execute, hindering further research in this area. The aim of this study was therefore to develop a deep learning framework capable of predicting polyethylene wear starting from kinematic and kinetic gait patterns, significantly lowering both computational costs and processing time compared to traditional FEA models.

METHODS: A published method was used to generate 314 variations of ISO14243-3(2014) anterior/posterior translation, internal/external rotation, flexion/extension, and axial loading time series, and a validated FEA model was used to calculate linear wear distribution on the polyethylene liner[2]. A deep learning model was then developed to predict linear wear, as an image, using gait patterns as input (**Figure 1**). Since predicting images from time series is a challenging task, we quantized each pixel value to fixed increments, transforming the problem from a regression into a pixel-wise classification task (**Figure 2A**). The dataset was then split into a training/validation/test set (60% - 20% -20%), and the model trained using categorical cross entropy as loss function. Model performance on the test set was evaluated using mean absolute percentage error (MAPE) between the deep learning model and the FEA model predictions. For both the medial and lateral wear areas, we evaluated the length, width, area, and the location of the centroids of the wear scar areas (**Figure 2B**).

RESULTS: For the medial and lateral wear areas: MAPE values remained under 3% and 6% respectively for the wear scar's width and length measurements, below 6% for the area of the wear scar, and below 1% for the mean distance between wear scar centroids (**Table 1**).

CONCLUSION: This study presents a novel approach to rapidly predict polyethylene wear in TKR, using deep learning to generate a surrogate model from FEA simulations. Next steps include exploring methodologies that do not rely on a pixel-wise discretization approach, as well as the incorporation of patient data. This method could enable the early detection of gait patterns that would put a patient at high risk for implant failure, giving clinicians a chance for early intervention.

References:
1 AJRR. (AAOS), (2020)
2 Mell, S. P. *et al. Journal of Orthopaedic Research* 38, 1538–1549 (2020)

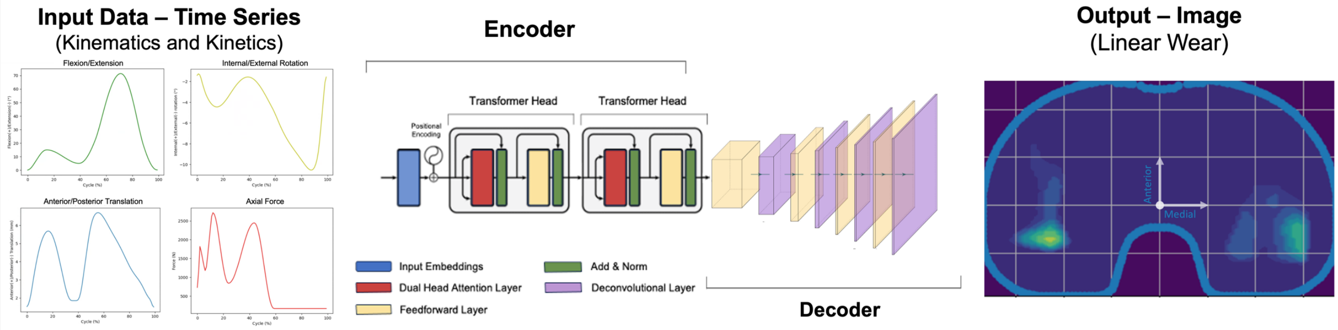

Figure 1: The proposed model consists of a U-net architecture incorporating a dual-head transformer encoder to discern temporal dependencies within the multivariate time series and deconvolutional layers in the decoder to ensure the reconstruction of image data. 314 input timeseries were normalized to 100 points, resulting in a total shape of 314x100x4. The model outputs a 100×100 pixel linear wear map prediction, in increments of 0.005mm.

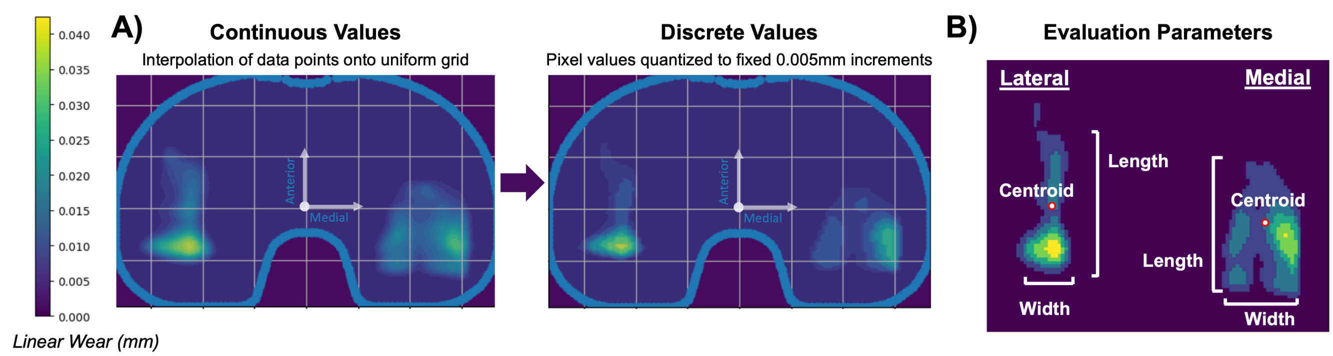

Figure 2: A) Linear wear predictions from the FEA model were interpolated onto a 100×100 grid (left) then each pixel value was quantized to fixed increments (right), transforming the model from a regression into a pixel-wise classification task. An increment of 0.005mm was chosen to ensure sensitivity of the predictions without excessively increasing the number of pixel-wise classes. **B)** Model performance on the test set was assessed using the mean absolute percentage error (MAPE), comparing the deep learning model's predictions with the gold standard FEA simulations' outputs. Evaluation parameters for both medial and lateral wear areas included length, width, area, and centroid location.

Table 1: Summary of mean average percentage error (MAPE) values for wear scar width, length, area, and centroid locations in medial and lateral wear scars.

Parameter	Mean Average Percentage Error (MAPE)
Width (Lateral)	2.92%
Length (Lateral)	5.26%
Area (Lateral)	5.35%
Centroid Location (Lateral)	0.39%
Width (Medial)	1.22%
Length (Medial)	2.28%
Area (Medial)	5.64%
Centroid Location (Medial)	0.57%