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DATA-DRIVEN BONE REMODELLING AFTER SCREW INSERTION

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1 INTRODUCTION

Computational approaches are powerful tools for studying biological processes like bone remodeling, helping to inform clinical decisions, such as predicting the outcomes of interventions like fracture repair. However, traditional methods like the Finite Element Method (FEM), while reliable, can be computationally expensive, especially in iterative processes like those used in bone remodeling simulations. Recent advances have shown that data-driven approaches can provide accurate representations of trabecular bone structures in a fraction of the time required by conventional methods via surrogate models [1]. In this study, the effects of screw insertion in the healing of calcaneal fractures on bone density distribution are studied using neural networks to accelerate the prediction process.

2 MATERIALS AND METHODS

The finite element method was employed was as a solver for the bone remodelling process in the gathering of training data,

The calcaneus was modelled as shown in Figure 1. The angles and magnitudes of each load were based on the literature [2] and kept constant and proportional. For simplicity the screw was considered to be solid, and the material was Ti-6Al-4V. The fractured was modelled with a very low modulus (1e-3 GPa).

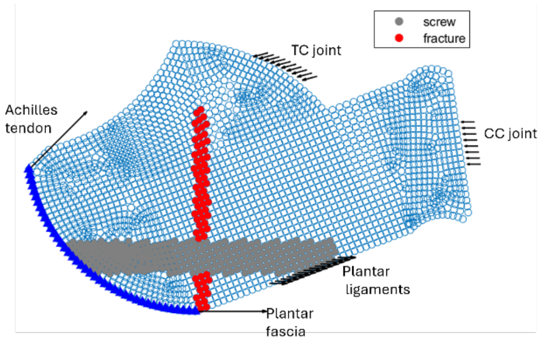

Figure 1 – Computational model of the calcaneus displaying the biomechanical loads, the screw and the fracture

The neural network structure was a multi-layer perceptron (MLP) with several parameters being varied in order to obtain the best model, namely, the activation function of the hidden layers, the number of hidden layers and the size of the hidden layers.

The network takes information regarding the most prevalent load case, the geometry of the bone and the screw and fracture. In total 16 parameters are used to quantify the model features: angle αj of each of the 5 biomechanical loads in agreement with the model, horizontal stretch dx and vertical stretch dy which quantify the anatomical variations of the model; xj and yj coordinates of the insertion point of the screw, xk and yk coordinates of the end of the screw, screw diameter, xl and yl coordinates of the beginning of the fracture, xm and ym coordinates of the end of the fracture. A total of 18 inputs are necessary, which are the 16 inputs to label the model and the coordinates xi and yi of the point of interest being predicted. The output is the density ρi of the point of interest.

The Adam optimizer was used to train the network. The batch size and learning rate were also tuned.

3 RESULTS AND DISCUSSION

Some neural predictions are shown in Figure 2 as well as the histogram for the histogram of the difference between targets and outputs.

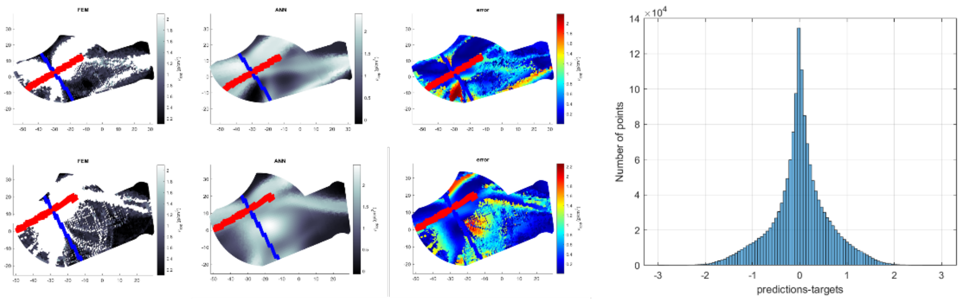

Figure 2 – Neural network predictions and error distribution histogram

The neural network produces a smoother density field compared to the output from the FEM, functioning as an approximation of the bone density distribution. However, due to the high variability caused by fracture location and screw positioning, some load cases result in different density alterations depending on these factors. As a result, the predicted density field for such cases may be less precise or well-defined. When the trabecular distribution closely resembles that of the intact bone model, the quality of the predictions improves significantly. These observations align with previous findings by the authors, where neural networks were shown to effectively model the influence of geometries and load cases [1].

According to the analysis, the median error in prediction is close to zero. Additionally, 39.96% of the points were predicted with an absolute error less than 0.2 g/cm^3, and 66.77% with an error less than 0.5 g/cm^3. This demonstrates that the neural networks are suitable surrogate models for FEM, as the variations in bone density within these error margins have minimal impact on the overall modulus of the bone. The discrepancies between the network's output and the target values are also partly due to the smoother density field generated by the neural network.

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