Clinical Application of CT-image Based Finite Element Method Combined with Machine Learning to Assessment of Bone Fracture

Shun Wu[1] and Todo Mitsugu[2]
[1]*Interdisciplinary Graduate School of Engineering, Kyushu University*
[2]Research Institute for Applied Mechanics, *Kyushu University*
Kasuga-koen, Kasuga, Fukuoka 816-8580, Japan

Abstract
In order to approach clinical vertebral body strength (BS) prediction quickly, it is necessary to combine empirical research with machine learning methods using multiple vertebral features to develop a BS evaluation methodology with the high accuracy. This research simulated BS by computed tomography based finite element method (CT-FEM). Then, BS-related morphological and material inhomogeneous features of vertebral bodies were collected to train six prevalent machine learning models. An empirical model was given based upon previous research. Compared with empirical model, logistic regression preformed most applicable.

1. Introduction

With the development of computed tomography based finite element method (CT-FEM), its accuracy of predicting vertebral body strength (BS) has been proven by some researches. [1] In order to approach the BS prediction quickly, it is useful to investigate the determinants that influence the BS value prediction in CT-FEM.

According to our previous research, CT-FEM predicted BS was mainly decided by $\mathrm{CALnVR}_{low\text{-}BMD}$, minimal vertebral cross-sectional area (MinCSA) adjusted logarithmic low volumetirc bone mineral density (vBMD) volume ratio, especially when vBMD<0.05 mg/mm^3 (see Eq. 1).

$$\mathrm{CALn}VR_{low-BMD} = (MinCSA) \cdot \left(\left| ln \frac{V_{low-BMD}}{V_{vertebra}} \right|\right) \quad \text{(Eq. 1)}$$

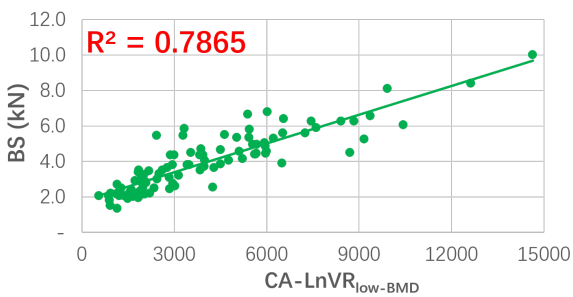

Figure 1. CALnVRlow-BMD VS vertebral strength.

This empirical model incorporates a vertebral morphological feature, MinCSA, and the material inhomogeneity feature. The high correlation has shown in Figure 1.

However, there are many other BS related features in the view of bone morphology and material homogeneities, such as vertebral height and the second lumber areal BMD (L2 aBMD). [2] It is very hard to connect them with $\mathrm{CALnVR}_{low\text{-}BMD}$ for improving BS predictor performance. The prevalent data-analysis method, machine learning (ML), has been widely used to look for the inner connection within complex features. Thus, the objective of this research is to combine the empirical research with machine learning methods using multiple vertebral features to develop a BS evaluation methodology with the high accuracy.

2. Method

2.1. Vertebral Strength Simulation

Department of neurosurgery, Inazawa Community Hospital supplied CT images of 88 patients, aged from 42 to 96. YAM ranged from 32 to 142. 100 vertebrae without surgical treatment or fractures were selected. All of them located from the eleventh thoracic (T11) to the third lumber (L3). Mechanical Finder Clinic (MFC, Research Center of Computational Mechanics, RCCM), was used to extract vertebral bodies without pedicle and to generate meshing elements. Then, the vBMD of elements was transferred from CT-values from voxels. Material properties was calculated according to Keyak's formulae. [3] The load of axial compression was applied by MFC automatically. The BS was defined as the onset loading raising at least one solid element damaged in MFC.

2.2. BS-related Features Collections

Mechanical Finder 10 (MF10, RCCM) was used to study the BS-related morphological features and material inhomogeneous features of vertebral bodies further. 100 vertebrae were selected to reproduce vertebral bodies in MF10. Mesh size and shape were determined as 1 mm and tetrahedron, respectively. The methodology of material property arrangement was same with that of MFC. The BS-related features evaluated in MF10 were: total volume of vertebral body, the MinCSA along the axial direction, vertebral height in anterior end (Height-A), in central position (Height-C) and in posterior end (Height-P), low-vBMD (0-0.05 mg/mm^3) volume, low-vBMD volume ratio (VR), logarithmic VR and CALnVR$_{\text{low-BMD}}$. Additionally, five features that likely correlate to BS considered in this research were gender, age, L2 aBMD, Young Adult Mean of lumber (YAM lumber) and YAM femur. Overall, 14 features.

2.3. Empirical Model VS Machine Learning

The empirical model was given as Eq. 2.

$$\mathrm{BS} = a \cdot \mathrm{CALn}VR_{low-BMD} + b \qquad \text{(Eq. 2)}$$

Where 'a' and 'b' are coefficient and bias respectively.

This study defined BS prediction as a univariate classification problem. A vertebra was classified as healthy, when its strength more than 2500N, otherwise as weak state. We applied most common but vigorous ML models. They were logistic regression (LR), decision tree (DT), linear support vector machine by soft margin classification (SVM), random forest (RF) and voting classifier (VC). For each model, the parameters has been tuned finely to avoid overfitting. The classification accuracy of empirical model only and ML models were evaluated using cross validation of 5 folds by 'accuracy' scoring. Their mean accuracy percentage and standard deviation were listed in Table 1.

Table 1. Accuracy of empirical model & ML models

Model name	Mean accuracy (%)	Std accu(%)
Empirical Model Only	83.83	0.06
Logistic Regression	85.78	0.07
Decision Tree	82.94	0.07
Linear SVM	79.72	0.09
Random Forest	79.98	0.04
Voting Classifier	77.72	0.10

3. Result & Discussion

Table 1 display the mean accuracy for every model clearly. Our empirical model only had a high prediction accuracy. Logistic Regression slightly improved the result, while other ML models no better than empirical model only. Since empirical model and logistic regression are typically linear classifier, meanwhile decision tree, random forest and voting are more common on non-linear classification, it may suggest that BS maybe a linear superposition within some BS-related features. Next, the deep learning will be applied to improve the accuracy. The mis-predicted vertebra will be selected to dig more BS-related features.

Acknowledgment

I appreciate Todo Mitsugu sensei giving me such a chance to learn and apply ML in the research.

Reference

[1] P.K. Zysset, E. Dall'Ara, P. Varga, D.H. Pahr, *Bonekey. Rep*. **2013**, *2*, 386.

[2] J.M. Buckley, K. Loo, J. Motherway, *Bone*. **2007**, *40*, 767.

[3] J.H. Keyak, S.A. Rossi, K.A. Jones, H.B. Skinner, *J. Biomech*. **1997**, *31*, 125.

Email: wu.shun.393@s.kyushu-u.ac.jp