

Predicting Magnetic Resonance Imaging Results using Dynamic Lumbar Skin Strain Fields

Jordan Ryan¹, Matt Hancock¹, David T. Fullwood¹, Ulrike H. Mitchell¹, Anton E. Bowden¹
¹Brigham Young University, Provo, UT, USA
 Jryan21@byu.edu

Disclosures: J. Ryan: None. M. Hancock: None. D.T. Fullwood: 4; Sensable Technologies. U.H. Mitchell: None. A.E. Bowden: 4; Sensable Technologies.

INTRODUCTION:

Chronic low back pain (cLBP) is a widespread, chronic pain condition which inhibits one’s ability to perform simple daily tasks both in the workplace and in private life. An array of 16 nanocomposite high-deflection strain gauges was used to measure dynamic skin strain fields in the lumbar region, in a study comparing adults who have chronic low back pain to asymptomatic controls. Biomechanics biomarkers from the data were semi-automatically identified and processed, and deep learning models were applied to predict magnetic resonance imaging (MRI) results, including specific spinal levels of degenerated discs, endplate defects, modic changes, stenosis, and facet changes in a population of cLBP and asymptomatic controls.

METHODS:

Biomechanics data based on dynamic skin strain fields was collected from 632 subjects (482 cLBP, 150 asymptomatic control). MRI Data was collected on a subset of 262 of these subjects 142 cLBP, 120 asymptomatic controls, 140 males, 122 Females) using a Siemens 3T MAGNETOM Vida scanner according to the standardized NIH BACPAC consortium imaging protocol and then scored by board-certified radiologists using the UCSF REACH scoring system, which includes identification of the presence and grade of degenerative features in the discs, vertebrae, endplates, and facets, as well as the presence and grade of spinal stenosis at each spinal level. Each subject performed a series of 13 different movements during which the dynamic, time-dependent skin strain fields in the lumbar spine region were sampled at 50 Hz. Biosignal features from each of the sensors during each of the movements were processed and extracted from each subject’s collected data (2,238 features per subject), then used as inputs to deep learning models for two prediction tasks: classifying whether a subject had chronic low back pain and predicting binary MRI outcomes indicating vertebral, disc, facet, or stenosis defects at each level in the lumbar spine. A feed-forward neural network was trained separately for each task, with the cLBP model performing binary classification (either chronic or control) and the MRI model performing multi-label binary classification across all defect types (presence or absence of a defect at each level). Each model was trained using data from 80% of the subjects and tested on the remaining 20%. Performance was evaluated over 100 randomized train/test splits using class-specific accuracy metrics and confusion matrices, both per-label and aggregated.

RESULTS:

The cLBP classification model achieved an average prediction accuracy of 85.9%, with a true positive rate of 89.8% and a true negative rate of 69.9% as shown in Figure 1. For the MRI defect prediction task, the multi-label model achieved an overall correct classification rate of 70.2% across all vertebral, disc, facet, and stenosis outputs. True negatives were predominant across most outputs, particularly in stenosis-related labels, while disc and facet predictions showed higher false negative rates. Per-label performance varied, with some vertebral levels achieving high specificity, whereas certain disc and facet levels exhibited greater prediction difficulty as shown in Figure 2.

DISCUSSION:

Despite the relatively small cohort (262 subjects), the present results demonstrate the feasibility of using dynamic, biomechanical data from the wearable skin strain sensor system to provide preliminary screening for spinal level-specific degenerative defects, including disc degeneration, modic changes, endplate defects, facet degeneration, and spinal stenosis. The biomechanical connection between anatomical defects and spinal motion has been well-established in the biomechanics literature but has primarily been based on cadaver and FEA studies. Geometric and material factors that can be measured on MRI are not the only factors which affects spinal motion, thus a perfect correspondence is not anticipated to be possible. However, there is a substantial difference in cost and accessibility between an MRI scan costing hundreds of dollars and specialized equipment versus the wearable nanocomposite sensor array (~\$8 in material costs) which is interpreted automatically using a smartphone app. The wearable sensor array was also highly accurate in correctly distinguishing chronic low back pain subjects from asymptomatic controls, highlighting the promise of objective, wearable sensors as cLBP assessment tools.

SIGNIFICANCE:

A low-cost wearable device was able to predict spinal level-specific degenerative features with high levels (>70%) of accuracy and specificity (as compared to blinded, objective MRI scoring) using a deep-learning model, opening the door for inexpensive and accessible pre-screening of individuals with back pain.

ACKNOWLEDGEMENTS: The MRI REACH scoring was performed by Remi Lobo (U Michigan) and Thomas Link (UCSF), whose help is deeply appreciated. This research was supported by the NIH through the NIH HEAL Initiative, under award number 1UH3AR076723-01.

IMAGES AND TABLES:

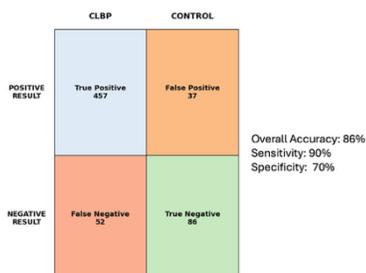


Figure 1: The “confusion matrix” assessing the ability of the wearable sensor array + deep learning model was able to predict whether a subject had cLBP or was an asymptomatic control with 86% accuracy at a high sensitivity (90%) and specificity (70%)

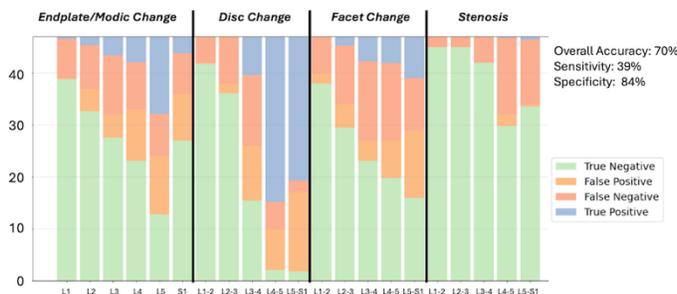


Figure 2: Confusion matrix data assessing the ability of the wearable sensor array + deep learning model to predict MRI-measured degenerative changes in spinal architecture at each spinal level due to endplate or modic changes, intervertebral disc degeneration, degenerative facet changes, or spinal stenosis.