Phenotyping Low Back Pain from Video Capture using Computer Vision and Machine Learning

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Introduction: Low back pain (LBP) is a global leading cause of disability. Physical activity and exercise tailored to individual needs is the main pillar of LBP management. Access to tailored physical activity and exercise protocols is clinically challenging given the multifactorial nature of LBP and classification complexity. Technologies such as artificial intelligence (AI) have been deployed to phenotype LBP previously. However, the contemporary AI models rely on data obtained from additional equipment (e.g. sensors) increasing the cost and acquisition complexity thus posing a challenge to clinical adoption.

Purpose/Aim: 1) Develop a proof-of-concept, AI-based automated classifier to phenotype LBP based on physical characteristics obtained from video; and 2) Assess its criterion validity, accuracy, sensitivity and specificity.

Materials and Methods: Convolutional Neural Networks (CNNs) HigherHRNet 'bottom-up' human pose estimation model architecture was initially trained to detect 17 human joints (keypoints) using of-the-shelf MS-COCO dataset containing videos of 250,000 individuals. Three keypoints (base of the neck, hip and ankle) were selected to extract features (movement angle and speed) considered clinically important during forward spine bend to phenotype LBP into commonly seen flexion motor control- and movement- impairment (MCI and MI, respectively). The 3 keypoint pose estimation model was then trained using feedforward neural networks machine learning tool applied to a video dataset of 83 individuals (47 females) with LBP, classified into MCI/MI subsets independently by two expert physiotherapists. The pose estimation model criterion validity was assessed by calculating mean square error (MSE) between the forward bend angle derived from the pose estimation and synchronised 3-dimensional motion capture using 75% of the LBP dataset (n=62). The classification accuracy, sensitivity and specificity were evaluated using the angle and speed of movement assessed separately and combined. The accuracy was assessed by calculating the proportion of predictions correctly assigned against the clinical judgement as gold standard. Sensitivity and specificity were assessed by calculating the proportion of true positive and true negative detections, respectively.

Results: High criterion validity with MSE score of 0.35 degrees was achieved. Classification accuracy based on angle alone produced accuracy of 93.98%, and sensitivity/specificity of 96.49% and 88.46%, respectively. Combining angle and speed reduced the accuracy and sensitivity slightly (92.77% and 92.98%, respectively) but increased the specificity (92.31%).

Conclusion(s): A proof-of-concept AI-based automated classifier to phenotype LBP based on performance of forward spine bend captured on video was developed and reached acceptable criterion validity. Classification accuracy, sensitivity and specificity varies based on the features selected, however, appears comparable with previously published inter-examiner agreement of trained clinicians thus demonstrating potential for clinical utility. Establishing classifier sensitivity to change in performance over time may be required to ensure responsiveness.

Keywords: low back pain; computer vision; automated classification