

## Research Article



# Predicting Trunk Muscle Activity in Chronic Low Back Pain: Development of a Supervised Machine Learning Model

Sara Salamat<sup>1</sup> , Vahideh Montazeri<sup>2</sup> , Saeed Talebian<sup>3\*</sup>

1. Behbahan Faculty of Medical Sciences, Behbahan, Iran.

2. Smart University of Medical Sciences, Tehran, Iran.

3. Department of Physiotherapy, School of Rehabilitation, Tehran University of Medical Sciences, Tehran, Iran.

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Artificial intelligence; Machine learning; Muscle activity**ABSTRACT****Introduction:** Recently, machine learning adoption has significantly increased across various applications, including the prediction of diseases based on a person's clinical profile. Accordingly, this study develops and evaluates a supervised machine learning method to predict trunk muscle activity in people with chronic low back pain.**Materials and Methods:** This was a secondary data analysis from a subgroup of people with nonspecific chronic low back pain. The correlation between labeled data and the output data of muscle activity level was measured through surface electromyography. The result showed a good correlation, suggesting the potential utility of this approach in distinguishing individuals with low back pain from pain-free controls.**Results:** To validate the performance of the developed machine learning, the results were compared with the SPSS software, version 17. The model's predictive performance was further assessed using various evaluation methods, including the area under the receiver operating characteristics curve. The study's findings indicate that the model achieved area under the curve values ranging from 0.5 to 0.9 across all muscles and different tasks for people with back pain. In contrast, the pain-free group exhibited area under the curve values between 0.4 and 0.8.**Conclusion:** The supervised machine learning approach using logistic regression may offer clinically meaningful predictions in defining the differences in trunk muscle activity between individuals with non-specific chronic low back pain and pain-free controls. While the obtained results demonstrate promise, further studies need to enhance the model's performance and achieve a more accurate estimation of muscle activity levels.**\* Corresponding Author:****Saeed Talebian, PhD.****Address:** Department of Physiotherapy, School of Rehabilitation, Tehran University of Medical Sciences, Tehran, Iran.**Tel:** +98 (936) 9104008**E-mail:** [talebiam@tums.ac.ir](mailto:talebiam@tums.ac.ir)Copyright © 2025 Tehran University of Medical Sciences. Published by Tehran University of Medical Sciences  
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## Introduction

**L**ow back pain (LBP) is a major global health leading to ongoing symptoms, poor quality of life, work performance, and social engagement with an average lifetime prevalence of 30% among adults [1]. While most individuals with low back pain experience spontaneous improvement or respond to treatments within a few weeks [2], a subset of people may develop chronic low back pain (CLBP) and despite recovery, few people still experience recurring episodes of LBP [3]. Only 15% of LBP cases have been identified to have specific underlying causes [4] and in the remaining 85% the cause is unknown and LBP is non-specific [5].

One possible physical factor that can contribute to LBP is the alteration in the level of activity of trunk muscles during daily functions [6]. This variability changes the load distributions on spinal structures, leading to continuation and exacerbation of pain. Trunk muscles particularly back extensors, play a critical role in various spinal functions and postures. Previous studies indicate that surface electromyography can differentiate between individuals with CLBP and those without pain [7]. It helps to understand muscles' functions by recording their electrical activity during contractions and different tasks.

Subgrouping of people with non-specific CLBP (NSCLBP) based on common features provides a promising approach for tailoring personalized treatments [8]. Classification systems have shown that people with NSCLBP have different muscle activity among subgroups. For instance, the results of previous studies based on the O'Sullivan classification system have shown that those with active extension-related NSCLBP display higher superficial trunk muscles' activity compared to other subgroups, such as flexion-related or multidirectional back pain [7].

In the last decade, there has been a significant rise in the adoption of artificial intelligence (AI) specially machine learning (ML) technologies, across various applications [9-11]. ML helps in diagnosis and outcome prediction [12], which is increasingly being utilized for the early prediction of several diseases based on the clinical profile of patients. It also plays a vital role in developing healthcare systems that integrate various elements such as science, motivation, data science, and culture to promote improvement. Practically, by integrating various data sources with advanced ML algorithms to generate data-driven insights aimed at improving biomedical research, public health, and the quality of healthcare

services, these systems can be deployed in small clinics as well as major healthcare organizations [12]. The growing volume of data in the field of medical science now enables more precise and insightful analyses, leading to higher diagnosis accuracy [13], pattern detection, and treatment. Compared to traditional statistical methods, the predictive capabilities of ML methodologies in conjunction with professional insights can enhance the accuracy of clinical decision-making and consequently boost treatment outcomes. Among different ML methods, multivariate logistic regression (LR) is widely used to identify risk factors that predict the development of complications. While ML techniques have been successful in classifying conditions like liver disease, heart failure [14, 15], and lung diseases [16], their application in low back pain research has been limited.

To the best of our knowledge, no study has examined ML algorithms in specific sub-groups of people with NSCLBP and during different dynamic tasks; therefore, the primary objective of the present study is to develop and evaluate the predictive performance of a supervised ML (SML) algorithm to distinguish differences between trunk muscle's activity of a subgroup of people with NSLBP (active extension related LBP) and pain-free controls before and after physiotherapy intervention using some clinical data as predictor gathered in some functional tasks.

## Materials and Methods

### Primary data

The raw material for this study was the previous electromyography (EMG) data of 5 trunk muscles collected from 120 people with and without NSCLBP before and after 4-week exercise (stabilization vs movement control exercises) therapy [17]. In brief, the study included a sub-group of people with back pain who met the following criteria: Pain associated with lower lumbar extension or postures, persistent back pain for more than 3 months, Tampa scale of kinesiophobia scores <41, Oswestry disability index (ODI) <13, and STarT Back scores <4. Subjects excluded from the study were individuals with specific low back pain conditions, such as fractures, infections, and spondylolisthesis, a history of previous low back pain with radiating pain to the legs, and individuals who were currently pregnant. Pain-free people were excluded if they had pain during the last 2 years. The study was approved by the Ethics Committee of [Smart University of Medical Sciences](#) (Code: IR.SMUMS.REC.1402.025).

The EMG activity of lumbar multifidus (LM), iliocostalis lumborum pars thoracis (ICL), rectus abdominis (RA), external oblique (EO), and internal oblique (IO) [7] was evaluated using channel data link EMG system (Biometrics) at 1 kHz and bandwidth between 20-40 Hz, common mode rejection ratio >96 at 60 Hz, and input impedance >1012  $\Omega$ .

The raw data were full-wave rectified and smoothed with 50 ms and surface EMG data were normalized with 2 submaximal voluntary isometric contractions described elsewhere [18].

Measured tasks were standing with open and closed eyes, sit-to-stand, flexion relaxation ratio, and forward flexion. EMG activity of 10 ms of standing with eyes closed, 15 ms of double leg and single leg standing with eyes opened, and the transfer time between sit to stand was analyzed.

### Machine learning model

The logistic regression supervised ML (LR-SML) model was employed to predict the EMG changes in the mentioned tasks. Due to its interpretability and low computational cost, logistic regression is considered a suitable classification algorithm for high-dimensional data. It is a statistical method that predicts the probability of an outcome based on one or more predictor variables [19]. In supervised learning, the algorithm is trained on a labeled dataset where the input data and corresponding output are known, allowing the algorithm to learn the relationship between the input and output variables. In this study, the labeled/input data were ODI scores, pain scores, age, weight, height and body mass index (BMI). The predicted/output data were 5 trunk muscles' activity during standing, sit-to-stand (STS), forward flexion (FF), and flexion relaxation ratio (FRR) functions before and after the intervention.

The correlation between labeled data (pain and questionnaire scores, age, weight, height, BMI, and output data (EMG activity) was evaluated and the results showed a good correlation between clinical scores and muscle activity (primary output data).

The labeled data were used to create a training set for model development. During training the labeled data were arranged according to their priority and weight. The erroneous data was excluded and the ML software was trained until the error reached a sufficiently minimized state. After establishing a specific controlled matrix, an algorithm to determine the best estimate between inputs

and outputs was developed. The SML was employed using data from 80 people with NSCLBP (stabilization group and movement control group) and 40 pain-free controls. The accuracy percentage was calculated with the following Equation 1 [20].

$$1. \text{Accuracy} = \frac{\text{Number of correct classifications}}{\text{Number of total classification}} \times 100$$

The detection performance of the model was evaluated using two metrics sensitivity and specificity which are indicative of the model's ability to correctly reject negative false instances and avoid false positive detections respectively [21]. The Equations 2 and 3 of the metrics are as follows.

$$2. \text{Sensitivity} = \frac{TP}{TP+FN}$$

$$3. \text{Specificity} = \frac{TN}{TN+FP}$$

Accordingly, TP (true positive) indicates the number of correct predicted event values, TN (true negative) indicates the number of correct predicted non-event values, FP (false positive) indicates incorrectly predicted event values, and FN (false negative) indicates numbers of incorrect predicted non-events values.

The model's classification performance was evaluated using the F1 score. This metric combines precision (sensitivity) and recall (ability of the model to identify true positives) to assess the overall classification performance. F1 score ranges between 0 and 1, with 1 representing perfect classification and 0 indicating no correct classification [22]. The Equation 4 is as follows.

$$4. \text{F1 score} = 2 \times \frac{\text{Precision} + \text{Recall}}{\text{Precision} \times \text{Recall}}$$

The model's ability to predict outcomes was then evaluated by analyzing the area under the receiver operating characteristic curve (AUC-ROC). The AUC value ranges between 0 and 1 and serves as a measure of discrimination capability in models, where a higher AUC value signifies enhanced discriminatory power [23].

### Statistical analysis

The normality of variable distributions was evaluated using the Shapiro-Wilk test. For correlation analysis, the Pearson correlation coefficients were used and mean comparisons were conducted using the student's t-test, with a significance level set at  $P < 0.05$ . The statistical analysis was performed using SPSS software, version 17 (SPSS Inc., Chicago, IL, USA) and Excel.

## Results

Before writing the algorithm, the correlation between primary inputs and outputs was calculated and the results revealed a moderate to strong correlation between them (Table 1, Table S1).

Subsequently, the algorithm was written using supervised ML methods. In the results section, different metrics for verification and validation of this algorithm are used and discussed. Initially, a comparative analysis was conducted between the radial basis function network ML algorithm and logistic multi-regression in SPSS using labeled data for training and testing (Figure 1).

The results indicated a close correspondence between the actual data from SPSS and the predictive outputs generated by the algorithms. Subsequently, to evaluate the predictive performance of the algorithm, the receiver operating characteristic (ROC) curve was employed. This graphical representation illustrates the trade-off between sensitivity and specificity of a diagnostic test at various threshold levels, allowing assessment of the performance of a binary classification model without the need to select a specific threshold [24]. The ROC curve compares the diagnostic ability of a test to random chance, with a diagonal line indicating random guessing (Table 2).

The AUC is a measure employed to encapsulate the comprehensive diagnostic accuracy of a test within binary classification tasks. It ranges from 0 to 1, with 0

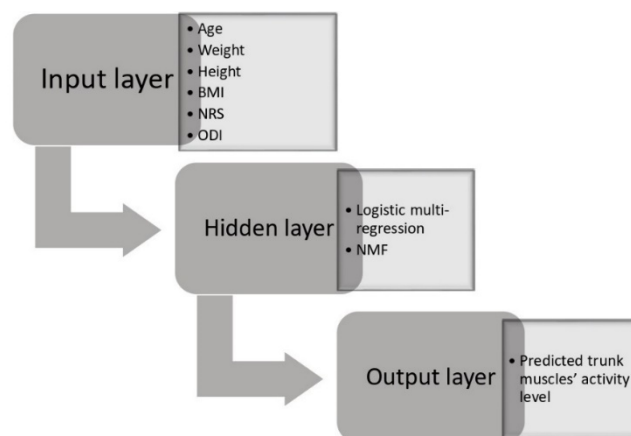
indicating a test that is completely inaccurate and 1 signifying an entirely accurate test.

For STS and FRR assessments, the AUC ranged from 0.4 to 0.9 across all muscles and groups, particularly notable in the healthy group. When comparing different standing positions (open vs closed and one leg vs double leg), the AUC values ranged from 0.50 to 0.88 in the stabilization and movement group. In contrast, the healthy group exhibited AUC values ranging between 0.6 to 1, especially during one-leg standing with open eyes, indicating that the classifier demonstrated good predictive performance overall and remains under clinical relevance in some other tasks (Table S2).

The average predicted trunk muscles' activity was assessed and compared with the mean activity of the actual primary output in the test session of the LR-SML algorithm (Table 3).

The result demonstrated high sensitivity (precision) and accuracy in predicting muscle activity in all tasks in three groups and during all tasks (Table S3).

To construct the predictive algorithm, we first calculated the correlation between pain and disability scores, age, weight, height, BMI, and trunk muscle activity. This calculation revealed a moderate to strong relationship. Then, logistic regression supervised ML (LR-SML) was utilized which is simple and widely used in the medical field. In supervised ML which is the most prevalent for training neural networks and decision trees, different algorithms are used to establish a function that links inputs (subjective scores) to the desired outcomes



**Figure 1.** Input layer (age, weight, height, BMI, NRS, ODI), hidden layer (equation of logistic multi-regression, NMF), output layer (predicted)

Abbreviation: BMI: Body mass index; NRS: Numeric rating scale; ODI: Oswestry disability index; NMF: Non-negative matrix factorization.

**Table 1.** Correlation between input and primary output layers (muscle activity) for supervised machine learning

Muscle Activity; Groups	Muscle	Age	Weight	BMI	Pain Before	ODI Before
Double leg open; Stabilization group	RA	-0.59**	-0.516**	-0.483**	-0.942**	-0.908**
	IO	-0.555**	-0.504**	-0.459**	-0.947**	-0.929**
	EO	-0.566**	-0.494**	-0.450**	-0.959**	-0.906**
	ML	-0.684**	-0.511**	-0.509**	-0.933**	-0.790**
	IC	-0.671**	-0.527**	-0.525**	-0.937**	-0.821**
Double leg open; Movement group	RA	-0.597**	-0.516**	-0.483**	-0.942**	-0.908**
	IO	-0.563**	-0.496**	-0.439**	-0.961**	-0.905**
	EO	-0.556**	-0.486**	-0.260	-0.963**	-0.905**
	ML	-0.643**	-0.233	-0.351*	-0.690**	-0.282
	IC	-0.690**	-0.324*	-0.516**	-0.776**	-0.422**
Double leg open; Pain-free group	RA	-0.811**	-0.825**	-0.715**		
	IO	-0.839**	-0.784**	-0.697**		
	EO	-0.719**	-0.848**	-0.648**		
	ML	-0.920**	-0.208	-0.350*		
	IC	-0.731**	-0.156	-0.114		
Transition phase open; Stabilization group	RA	-0.565**	-0.492**	-0.441**	-0.965**	-0.893**
	IO	-0.528**	-0.483**	-0.422**	-0.968**	-0.913**
	EO	-0.539**	-0.473**	-0.415**	-0.974**	-0.891**
	ML	-0.590**	-0.457**	-0.412**	-0.965**	-0.774**
	IC	-0.623**	-0.498**	-0.471**	-0.958**	-0.813**
Transition phase open; Movement group	RA	-0.552**	-0.483**	-0.426**	-0.971**	-0.888**
	IO	-0.544**	-0.482**	-0.428**	-0.972**	-0.894**
	EO	-0.520**	-0.459**	-0.393*	-0.981**	-0.884**
	ML	-0.554**	-0.244	-0.216	-0.794**	-0.395*
	IC	-0.600**	-0.313*	-0.293	-0.843**	-0.488**
Transition phase open; Pain-free group	RA	-0.739**	-0.831**	-0.644**		
	IO	-0.858**	-0.754**	-0.671**		
	EO	-0.791**	-0.772**	-0.617**		
	ML	-0.862**	-0.332*	-0.311		
	IC	-0.650**	-0.335*	-0.121		

Notes: Correlation coefficient = Pearson; \*P<0.05; \*\*P<0.01.



Abbreviations: RA: Rectus abdominis; IO: Internal oblique; EO: External oblique; ML: Multifidus; IC: Iliocostalis; BMI: Body mass index; ODI: Oswestry disability index.

(SEMG). Concerning this, to confirm the accuracy and validate the model, two distinct methodologies on statistical analysis platforms were implemented. Initially, the algorithms within SPSS were utilized to replicate the entire set of operations executed by the proposed model. Average values and the standard deviations for the absolute prediction errors and the differences were calculated. Additionally, the correlation between the predicted outcomes and the primary outcomes was assessed. Subsequently, the correlation of the predicted values from SPSS with the original dataset, as well as the correla-

tion of predicted values from the LR-SML software with the same dataset was constructed and determined. The analysis revealed a strong correlation between the two software programs. The findings also suggest that the performance of LR-SML and SPSS varied among individuals with LBP, and LR-SML showed a higher error rate across most parameters, while in the pain-free group, there was not a significant difference between the two software in most tasks (Table 4; Table S4).

**Table 2.** AUC-reciever operating characteristics of both software during functional tasks

Groups	Muscle	Eyes Closed Transition Phase		Eyes Open Transition Phase	
		AUC-LR	AUC-SPSS	AUC-LR	AUC-SPSS
Stabilization group	RAb	0.56	0.51	0.55	0.54
	RAa	0.53	0.52	0.56	0.55
	IOb	0.57	0.57	0.58	0.57
	IOa	0.56	0.57	0.57	0.58
	EOb	0.53	0.52	0.56	0.54
	EOa	0.53	0.52	0.49	0.48
	MLb	0.47	0.47	0.5	0.5
	MLa	0.46	0.47	0.5	0.5
	ICb	0.5	0.5	0.49	0.5
	ICa	0.5	0.5	0.49	0.5
Movement group	RAb	0.53	0.52	0.6	0.6
	RAa	0.53	0.52	0.6	0.6
	IOb	0.53	0.52	0.6	0.6
	IOa	0.54	0.52	0.6	0.6
	EOb	0.53	0.52	0.6	0.6
	EOa	0.57	0.57	0.6	0.6
	MLb	0.56	0.58	0.46	0.5
	MLa	0.56	0.58	0.52	0.78
	ICb	0.56	0.58	0.5	0.5
	ICa	0.56	0.58	0.5	0.5
Pain-free group	RA	0.57	0.56	0.65	0.65
	IO	0.74	0.74	0.53	0.65
	EO	0.43	0.43	0.5	0.5
	ML	0.52	0.5	0.65	0.49
	IC	0.46	0.46	0.71	0.96



**Table 3.** Performance parameters of logistic regression supervised machine learning for predicting Trunk muscles activity

Muscle Activity; Groups	Muscle	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1-Score
Double leg close; Stabilization group	RAb	0.9	0.91	90	0.92
	RAa	0.95	0.92	95	0.96
	IOb	0.93	0.92	92	0.94
	IOa	0.96	0.92	95	0.96
	EOb	0.96	0.92	95	0.96
	EOa	0.93	0.92	92	0.94
	MLb	0.96	1	97	0.93
	MLa	1	1	100	1
	ICLb	0.9	1	92	0.92
ICLa	0.9	1	92	0.93	
Double leg close; Movement group	RAb	0.96	0.92	95	0.96
	RAa	0.96	0.92	95	0.96
	IOb	0.96	0.92	95	0.96
	IOa	0.93	0.92	92	0.94
	EOb	0.96	0.92	90	0.96
	EOa	0.93	0.92	95	0.94
	MLb	0.90	0.91	92	0.93
	MLa	0.90	0.90	90	0.93
	ICLb	1	0.93	97	0.97
ICLa	0.90	0.90	90	0.93	
Double leg close; Pain-free group	RA	0.45	0.42	50	0.6
	IO	0.5	0.5	44	0.48
	EO	0.44	0.4	55	0.53
	ML	0.37	0.35	44	0.34
	IC	0.45	0.42	48	0.43



Abbreviations: RAb: Rectus abdominis before; RAa: Rectus abdominis after; IOb: Internal oblique before; IOa: Internal oblique after; EOb: External oblique before; EOa: External oblique after; MLb: Multifidus before; MLa: Multifidus after; ICLb: Iliocostalis before; ICLa: Iliocostalis after; FRR: Flexion relaxation ratio; STS: Sit to stand; FF: Forward flexion.

F1-score was employed as a statistical measure to evaluate the accuracy of our model. The outcomes revealed F1-scores ranging from 0.4 to 1 across all parameters and all groups, signifying the model's proficiency in accurately classifying true positive cases and actual positive cases.

### Discussion

In this study, an ML approach was employed to create a predictive model for estimating the activity level of trunk muscles in individuals with active extension nonspecific low back pain (AENSLBP) and pain-free groups using information from pain and disability scores, age, weight, height, and BMI. In the previous study [25], the LR-SML was employed for individuals with tinnitus to forecast brainwave patterns. The study demonstrated that the model was simple and effective in predicting the func-

tional profile of tinnitus using subjective scales and EEG data. In the present study, a similar model was applied.

Sensitivity and specificity metrics indicate how correctly the model identifies positive (true positive) and negative (true negative) classes, respectively. In this study, the values of sensitivity and specificity were high in testing dataset indicating that LR-SML has a good ability to accurately classify instances with a low rate of error. Moreover, the results of F1 scores observed for all tasks indicates the model's well performance in accurately predict positive instances while minimizing both false positives and false negatives.

In line with the findings of Kyzet et al. [26], which showed higher accuracy during isometric contractions compared to dynamic tasks, our results revealed lower prediction accuracy in more challenging tasks, such as

Table 4. Mean error of two software

Muscle Activity; Groups	Muscle	Mean difference	P	Muscle Activity; Groups	Muscle	Mean Difference	P
Double leg close; Stabilization group	RAb	2.03	0.00	Double leg open; Stabilization group	Rab	2.27	0.00
	RAa	2.82	0.00		Raa	0.93	0.00
	IOb	2.25	0.00		Iob	2.18	0.00
	IOa	0.98	0.00		IoA	1.57	0.001
	EOb	2	0.00		Eob	1.96	0.00
	EOa	2.95	0.00		Eoa	2.92	0.00
	MLb	4.86	0.00		MLb	1.53	0.00
	MLa	3.3	0.00		Mla	1.99	0.00
	ICb	3.31	0.00		Icb	2.99	0.00
ICa	2.85	0.00	Ica	2.88	0.00		
Double leg close; Movement group	RAb	2.63	0.00	Double leg open; Movement group	Rab	1.1	0.00
	RAa	3.72	0.00		Raa	1.1	0.04
	IOb	2.33	0.00		Iob	1.7	0.02
	IOa	1.1	0.00		IoA	0.8	0.11
	EOb	2.35	0.00		Eob	0.53	0.18
	EOa	3.74	0.00		Eoa	0.6	0.02
	MLb	2.21	0.04		MLb	2.94	0.00
	MLa	1.4	0.02		Mla	1.71	0.00
	ICb	2.04	0.04		Icb	3.22	0.00
ICa	3.24	0.00	Ica	2.4	0.00		
Double leg close; Pain-free group	RA	1.17	0.6	Double leg open; Pain-free group	RA	-1.4	0.32
	IO	1.29	0.06		IO	-2.39	0.14
	EO	5.45	0.02		EO	-0.74	0.36
	ML	1.43	0.10		ML	-0.28	0.49
	IC	2.86	0.10		IC	-0.36	0.56



Abbreviations: RAb: Rectus abdominis before; RAa: Rectus abdominis after; IOb: Internal oblique before; IOa: Internal oblique after; EOb: External oblique before; EOa: External oblique after; MLb: Multifidus before; MLa: Multifidus after; ICb: Iliocostalis before; ICa: Iliocostalis after; FRR: Flexion relaxation ratio; STS: Sit to stand; FF: Forward flexion.

one-leg standing with closed eyes. This suggests that additional input data may be necessary to enhance the performance. Previous research has highlighted that predicting pain incidence is challenging because of the intricate interplay between various factors [27].

Similarly, muscles within the musculoskeletal system are complex and challenging to model, and the static. Thus, Using the model in clinical devices presents a significant challenge [28]. The primary objective of this study was to provide clinicians with a means of estimating EMG activity without an electrode setup. This study aimed to find a method for accurately and efficiently predicting muscle activation using an ML model. Recently, ML models have been developed to estimate skeletal muscle activity without explicit modeling of the physical characteristics of muscles. However, an inverse muscle model has yet to be developed using an ML model. The

LR-SML model can offer the ability to predict muscle activity via subjective information.

The estimated EMG signals and real data showed that the designed model in some cases had slight differences; however, the pattern of the estimated signals was sufficiently similar to allow the students and clinicians to avoid EMG electrode setups in the laboratory and use LR-SML instead. However, the model is task specific and may require extensive data for a more generalized model.

Notably, most computational techniques for calculating muscle variables have inherent limitations in their analytical expressions and suffer from unrealistic assumptions in muscle models. The model parameters identified with measurements that are subject to error, such as the relative location between muscles and electrodes [26], variability in individuals' biological characteristics,



and activation patterns of muscles, require a continual optimization loop and result in estimated muscle activations that may not be entirely accurate [29]. The complex behaviors of muscles during dynamic tasks make them difficult especially for static models.

Results of the present study revealed that despite the higher error of the LR-SML in the LBP group compared with SPSS, it stands out for its simplicity and feasibility. Because an integral part of an ML algorithm is to be user-friendly and easily integrated into existing clinical procedures [30], the model's architecture was designed to be robust and stable, even when processing large data despite its accuracy, SPSS showed inconsistency in handling increased data volume and complexity.

## Conclusion

The results of the present study suggest that LR-SML may provide slight but clinically relevant, predictions for defining trunk muscle activity of people with AENSCLBP and pain-free controls.

Despite the promising results obtained, further studies are necessary to improve model's performance and have a better estimation of muscle activity level.

## Study limitations

The present study has several limitations. First, a specific dataset was used in this study, which may increase the risk that the results are population-specific and the prognostic factors may decrease generalizability in other populations. Second the model is task-based and it is not certain that the model can be used for other tasks. For a general model, a large amount of data is required. In addition, a homogenous subgroup of people with low back pain limits the generalizability of our findings; however, acceptable results during most tasks are promising.

Therefore, further research is needed to determine the generalizability of our findings to different populations and to explore the impact of these conditions on treatment outcomes.

## Ethical Considerations

### Compliance with ethical guidelines

The study was approved by the Ethics Committee of [Smart University of Medical Sciences](#) (Code: IR.SMUMS.REC.1402.025).

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## Authors' contributions

All authors contributed equally to the conception and design of the study, data collection and analysis, interpretation of the results, and manuscript drafting. Each author approved the submission of the final version of the manuscript.

## Conflict of interest

The authors declared no conflict of interest.

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## References

- [1] Andersson GB. Epidemiological features of chronic low-back pain. *Lancet*. 1999; 354(9178):581-5. [DOI:10.1016/S0140-6736(99)01312-4] [PMID]
- [2] Cho KH, Beom JW, Lee TS, Lim JH, Lee TH, Yuk JH. Trunk muscles strength as a risk factor for nonspecific low back pain: A pilot study. *Annals of Rehabilitation Medicine*. 2014; 38(2):234-40. [DOI:10.5535/arm.2014.38.2.234] [PMID]
- [3] Shim JG, Ryu KH, Cho EA, Ahn JH, Kim HK, Lee YJ, et al. Machine learning approaches to predict chronic lower back pain in people aged over 50 years. *Medicina*. 2021; 57(11):1230. [DOI:10.3390/medicina57111230] [PMID]
- [4] O'Sullivan P. It's time for change with the management of non-specific chronic low back pain. *British Journal of Sports Medicine*. 2012; 46(4):224-7. [DOI:10.1136/bjism.2010.081638] [PMID]
- [5] Gordon R, Bloxham S. A systematic review of the effects of exercise and physical activity on non-specific chronic low back pain. *Healthcare*. 2016; 4(2):22. [DOI:10.3390/healthcare4020022] [PMID]
- [6] van Dieën JH, Selen LP, Cholewicki J. Trunk muscle activation in low-back pain patients, an analysis of the literature. *Journal of Electromyography and Kinesiology*. 2003; 13(4):333-51. [DOI:10.1016/S1050-6411(03)00041-5] [PMID]
- [7] Salamat S, Talebian S, Maroufi N, Kalbassi G, Salamat D, O'Sullivan K. People with low back pain exhibit higher trunk muscle activity and impaired postural control during static and dynamic functional tasks: A cross-sectional study. *Journal of Applied Biomechanics*. 2023; 40(1):1-8. [DOI:10.1123/jab.2023-0033] [PMID]

- [8] Tagliaferri SD, Owen PJ, Miller CT, Angelova M, Fitzgibbon BM, Wilkin T, et al. Towards data-driven biopsychosocial classification of non-specific chronic low back pain: A pilot study. *Scientific Reports*. 2023; 13(1):13112. [DOI:10.1038/s41598-023-40245-y] [PMID]
- [9] Hartley T, Hicks Y, Davies JL, Cazzola D, Sheeran L. BACK-to-MOVE: Machine learning and computer vision model automating clinical classification of non-specific low back pain for personalised management. *PLoS One*. 2024; 19(5):e0302899. [DOI:10.1371/journal.pone.0302899] [PMID]
- [10] Kadhim MA. FNDSB: A fuzzy-neuro decision support system for back pain diagnosis. *Cognitive Systems Research*. 2018; 52:691-700. [DOI:10.1016/j.cogsys.2018.08.021]
- [11] Amorim P, Paulo JR, Silva PA, Peixoto P, Castelo-Branco M, Martins H. Machine learning applied to low back pain rehabilitation-a systematic review. *International Journal of Digital Health*. 2021; 1(1):10. [DOI:10.29337/ijdh.34]
- [12] Sidey-Gibbons JAM, Sidey-Gibbons CJ. Machine learning in medicine: A practical introduction. *BMC Medical Research Methodology*. 2019; 19(1):64. [DOI:10.1186/s12874-019-0681-4] [PMID]
- [13] Caldo D, Bologna S, Conte L, Amin MS, Anselma L, Basile V, et al. Machine learning algorithms distinguish discrete digital emotional fingerprints for web pages related to back pain. *Scientific Reports*. 2023; 13(1):4654. [DOI:10.1038/s41598-023-31741-2] [PMID]
- [14] Mizuguchi Y, Nakao M, Nagai T, Takahashi Y, Abe T, Kakinoki S, et al. Machine learning-based gait analysis to predict clinical frailty scale in elderly patients with heart failure. *European Heart Journal. Digital Health*. 2023; 5(2):152-62. [DOI:10.1093/ehjdh/ztad082] [PMID]
- [15] Yoon M, Park JJ, Hur T, Hua CH, Hussain M, Lee S, et al. Application and potential of artificial intelligence in heart failure: Past, present, and future. *International Journal of Heart Failure*. 2023; 6(1):11-9. [DOI:10.36628/ijhf.2023.0050] [PMID]
- [16] Hartman DJ. Applications of artificial intelligence in lung pathology. *Surgical Pathology Clinics*. 2024; 17(2):321-8. [DOI:10.1016/j.path.2023.11.013] [PMID]
- [17] Salamat S, Talebian S, Bagheri H, Maroufi N, Jafar Shaterzadeh M, Kalbasi G, et al. Effect of movement control and stabilization exercises in people with extension related non-specific low back pain- a pilot study. *Journal of Bodywork and Movement Therapies*. 2017; 21(4):860-5. [DOI:10.1016/j.jbmt.2017.02.005] [PMID]
- [18] Dankaerts W, O'Sullivan P, Burnett A, Straker L. Altered patterns of superficial trunk muscle activation during sitting in nonspecific chronic low back pain patients: Importance of subclassification. *Spine*. 2006; 31(17):2017-23. [DOI:10.1097/01.brs.0000228728.11076.82] [PMID]
- [19] Chen B. From logistic Regression to deep learning: Machine learning advances for credit card churn. *International Journal of Enhanced Research in Management & Computer Applications*. 2024; 13(2):31-5. [Link]
- [20] Rescio G, Leone A, Siciliano P. Supervised machine learning scheme for electromyography-based pre-fall detection system. *Expert Systems with Applications*. 2018; 100:95-105. [DOI:10.1016/j.eswa.2018.01.047]
- [21] Kutrani H, Eltalhi S, Ashleik N. Predicting factors influencing survival of breast Cancer patients using logistic regression of machine learning. Paper presented: 7th International Conference on Engineering & MIS. 11-13 October 2021; Almaty, Kazakhstan. [DOI:10.1145/3492547.3492590]
- [22] Jinri WM, Keikhosrokiani P, Abdullah NL. Machine learning algorithms for the classification of cardiovascular disease-A comparative study. Paper presented: International Conference on Information Technology (ICIT). 14-15 July 2021; Amman, Jordan. [DOI:10.1109/ICIT52682.2021.9491677]
- [23] Barbosa VP, Said dos Reis JL, von Zuben de Valega Negrão C, Barboza VR, Simoes Marcondes KC, Rezende EP, et al. Machine learning model to predict allocation of patients with chronic back pain for integrated practice units in a system of value-based health care. *medRxiv*. 2023. [DOI:10.1101/2023.1.05.23298111]
- [24] Rahman M, Hossain B, Sayed A, Thakur S. Assessment of liquefaction potential based on the logistic regression machine learning algorithm. Paper presented: 7th International Conference on Civil Engineering for Sustainable Development. 7-9 February 2024; Khulna, Bangladesh. [Link]
- [25] Mohsen S, Sadeghijam M, Talebian S, Pourbakht A. Use of some relevant parameters for primary prediction of brain activity in idiopathic tinnitus based on a machine learning application. *Audiology & Neuro-otology*. 2023; 28(6):446-57. [DOI:10.1159/000530811] [PMID]
- [26] Kizyte A, Lei Y, Wang R. Influence of input features and EMG type on ankle joint torque prediction with Support Vector Regression. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2023; 31:4286-94. [DOI:10.1109/TNSRE.2023.3323364] [PMID]
- [27] Joensuu L, Rautiainen I, Hautala AJ, Siekkinen K, Pirnes K, Tammelin TH. Prediction of multisite pain incidence in adolescence using a machine learning approach: A 2-year longitudinal study. *Health Science Reports*. 2024; 7(12):e70252. [DOI:10.1002/hsr2.70252]
- [28] Nasr A, Inkol KA, Bell S, McPhee J. InverseMuscleNET: Alternative machine learning solution to static optimization and inverse muscle modeling. *Frontiers in Computational Neuroscience*. 2021; 15:759489. [DOI:10.3389/fncom.2021.759489] [PMID]
- [29] Wu D, Yang J, Sawan M. Transfer Learning on Electromyography (EMG) tasks: Approaches and beyond. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2023; 31:3015-34. [DOI:10.1109/TNSRE.2023.3295453] [PMID]
- [30] Michelsen C, Jørgensen CC, Heltberg M, Jensen MH, Luchetti A, Petersen PB, et al. Machine-learning vs. logistic regression for preoperative prediction of medical morbidity after fast-track hip and knee arthroplasty-a comparative study. *BMC Anesthesiology*. 2023; 23(1):391. [DOI:10.1186/s12871-023-02354-z] [PMID]

**Table S1.** Correlation between input and primary output layers (muscle activity) for supervised machine learning

Muscle Activity; Groups	Muscle	Age	Weight	BMI	Pain Before	ODI Before
Double leg close; Stabilization group	RA	-0.591**	-0.518**	-0.493**	-0.936**	-0.921**
	IO	-0.562**	-0.512**	-0.462**	-0.945**	-0.923**
	EO	-0.566**	-0.494**	-0.450**	-0.959**	-0.906**
	ML	-0.684**	-0.511**	-0.509**	-0.933**	-0.790**
	IC	-0.562**	-0.517**	-0.525**	-0.927**	-0.821**
Double leg close; Movement group	RA	-0.597**	-0.516**	-0.483**	-0.942**	-0.908**
	IO	-0.574**	-0.503**	-0.464**	-0.955**	-0.906**
	EO	-0.569**	-0.496**	-0.453**	-0.957**	-0.907**
	ML	-0.654**	-0.532**	-0.527**	-0.941**	-0.842**
	IC	-0.645**	-0.530**	-0.531**	-0.942**	-0.844**
Double leg close; Pain-free group	RA	-0.847**	-0.790**	-0.714**		
	IO	-0.785**	-0.825**	-0.690**		
	EO	-0.838**	-0.784**	-0.691**		
	ML	-0.919**	-0.722**	-0.734**		
	IC	-0.859**	-0.807**	-0.762**		
Transition phase close; Stabilization group	RA	-0.709**	-0.474**	-0.401*	-0.894**	-0.745**
	IO	-0.528**	-0.483**	-0.422**	-0.968**	-0.914**
	EO	-0.539**	-0.473**	-0.415**	-0.974**	-0.892**
	ML	-0.649**	-0.491**	-0.472**	-0.948**	-0.787**
	IC	-0.623**	-0.498**	-0.471**	-0.958**	-0.815**
Transition phase close; Movement group	RA	-0.568**	-0.495**	-0.445**	-0.963**	-0.896**
	IO	-0.549**	-0.484**	-0.430**	-0.970**	-0.894**
	EO	-0.544**	-0.477**	-0.421**	-0.972**	-0.894**
	ML	-0.615**	-0.507**	-0.480**	-0.960**	-0.840**
	IC	-0.606**	-0.518**	-0.492**	-0.960**	-0.856**
Transition phase close; Pain-free group	RA	-0.836**	-0.783**	-0.686**		
	IO	-0.900**	-0.698**	-0.658**		
	EO	-0.811**	-0.775**	-0.645**		
	ML	-0.898**	-0.721**	-0.683**		
	IC	-0.849**	-0.800**	-0.728**		
One leg open; Stabilization group	RA	-0.535**	-0.471**	-0.405**	-0.978**	-0.877**
	IO	-0.504**	-0.463**	-0.390*	-0.980**	-0.897**
	EO	-0.514**	-0.455**	-0.384*	-0.984**	-0.875**
	ML	-0.525**	-0.418**	-0.346*	-0.975**	-0.755**
	IC	-0.583**	-0.472**	-0.427**	-0.970**	-0.802**
One leg open; Movement group	RA	-0.504**	-0.447**	-0.367*	-0.987**	-0.859**
	IO	-0.530**	-0.471**	-0.410**	-0.978**	-0.886**
	EO	-0.494**	-0.440**	-0.362*	-0.988**	-0.867**
	ML	-0.501**	-0.247	-0.191	-0.837**	-0.448**
	IC	-0.549**	-0.305	-0.260	-0.871**	-0.518**
One leg open; Pain-free group	RA	-0.907**	-0.669**	-0.633**		
	IO	-0.849**	-0.745**	-0.645**		
	EO	-0.730**	-0.751**	-0.527**		
	ML	-0.766**	-0.405**	-0.250		
	IC	-0.494**	-0.232	0.046		
One leg close; Stabilization group	RA	-0.535**	-0.471**	-0.405**	-0.978**	-0.877**
	IO	-0.504**	-0.463**	-0.390*	-0.978**	-0.897**
	EO	-0.681**	-0.463**	-0.389*	-0.904**	-0.742**
	ML	-0.617**	-0.474**	-0.440**	-0.958**	-0.780**
	IC	-0.617**	-0.473**	-0.440**	-0.958**	-0.780**
One leg close; Movement group	RA	-0.541**	-0.475**	-0.412**	-0.976**	-0.882**
	IO	-0.526**	-0.467**	-0.401*	-0.980**	-0.880**
	EO	-0.517**	-0.457**	-0.387*	-0.983**	-0.877**
	ML	-0.582**	-0.485**	-0.441**	-0.972**	-0.829**
	IC	-0.567**	-0.489**	-0.442**	-0.975**	-0.845**
One leg close; Pain-free group	RA	-0.873**	-0.740**	-0.674**		
	IO	-0.858**	-0.687**	-0.582**		
	EO	-0.817**	-0.769**	-0.640**		
	ML	-0.872**	-0.718**	-0.637**		
	IC	-0.839**	-0.792**	-0.696**		

Muscle Activity; Groups	Muscle	Age	Weight	BMI	Pain Before	ODI Before
STS; Stabilization group	RA	-0.597**	-0.516**	-0.483**	-0.942**	-0.908**
	IO	-0.557**	-0.493**	-0.449**	-0.963**	-0.903**
	EO	-0.548**	-0.480**	-0.431**	-0.966**	-0.904**
	ML	-0.056	0.355*	0.350*	0.100	0.580**
	IC	-0.199	0.239	0.222	-0.087	0.417**
STS; Movement group	RA	-0.597**	-0.516**	-0.483**	-0.942**	-0.908**
	IO	-0.552**	-0.471**	-0.434**	-0.969**	-0.877**
	EO	-0.536**	-0.472**	-0.419**	-0.971**	-0.903**
	ML	0.543**	0.645**	0.653**	0.760**	0.933**
	IC	0.547**	0.660**	0.679**	0.729**	0.918**
STS; Pain-free group	RA	-0.917**	-0.707**	-0.710**		
	IO	-0.905**	-0.424**	-0.440**		
	EO	-0.870**	-0.279	-0.334*		
	ML	0.669**	0.952**	0.871**		
	IC	0.656**	0.945**	0.902**		
FRR; Stabilization group	ML	-0.006	0.268	0.091	0.784**	0.932**
	IC	-0.006	0.268	0.091	0.784**	0.932**
FRR; Movement group	ML	-0.008	0.273	0.093	0.786**	0.932**
	IC	-0.008	0.273	0.093	0.786**	0.932**
FRR; Pain-free group	ML	0.797**	0.885**	0.881**		
	IC	-0.745**	0.157	0.037		

Notes: Correlation coefficient = Pearson, \*P<0.05; \*\*P<0.01.

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Abbreviations: RA: Rectus abdominis; IO: Internal oblique; EO: External oblique; ML: Multifidus; IC: Iliocostalis; BMI: Body mass index; ODI: Oswestry disability index.

**Table S2.** AUC-ROC of both software during double leg standing with eye open and closed, flexion relaxation ratio, forward flexion, and sit to stand before and after exercise in people with AENSLBP and pain-free controls

Groups	Muscle	Eyes Closed Double Leg		Eyes Open Double Leg	
		AUC-LR	AUC-SPSS	AUC-LR	AUC-SPSS
Stabilization group	RAb	0.55	0.55	0.53	0.52
	RAa	0.55	0.55	0.53	0.52
	IOb	0.53	0.52	0.53	0.52
	IOa	0.53	0.52	0.59	0.58
	ERb	0.53	0.52	0.53	0.52
	EOa	0.55	0.55	0.53	0.52
	MLb	0.51	0.49	0.52	0.5
	MLa	0.5	0.5	0.5	0.5
	ICb	0.5	0.5	0.51	0.5
Movement group	ICa	0.5	0.5	0.49	0.5
	RAb	0.47	0.47	0.66	0.67
	RAa	0.45	0.45	0.66	0.66
	IOb	0.47	0.48	0.6	0.61
	IOa	0.47	0.48	0.6	0.6
	EOb	0.47	0.48	0.6	0.6
	EOa	0.45	0.45	0.64	0.64
	MLb	0.47	0.45	0.48	0.5
	MLa	0.48	0.47	0.61	0.58
Pain-free group	ICb	0.48	0.47	0.48	0.51
	ICa	0.47	0.45	0.55	0.55
	RA	0.57	0.56	0.53	0.53
	IO	0.74	0.74	0.42	0.44
	EO	0.43	0.43	0.43	0.4
	ML	0.52	0.5	0.43	0.4
	IC	0.46	0.46	0.58	0.54

Groups	Muscle	Eyes Closed One Leg		Eyes Open One Leg	
		AUC-LR	AUC-SPSS	AUC-LR	AUC-SPSS
Stabilization group	RAb	0.58	0.58	0.53	0.52
	RAa	0.6	0.6	0.59	0.58
	IOb	0.62	0.63	0.61	0.61
	IOa	0.61	0.63	0.61	0.6
	EOb	0.66	0.68	0.58	0.57
	EOa	0.62	0.63	0.58	0.58
	MLb	0.51	0.52	0.56	0.58
	MLa	0.53	0.55	0.6	0.6
	ICb	0.5	0.5	0.55	0.58
	ICa	0.56	0.58	0.6	0.61
Movement group	RAb	0.6	0.6	0.61	0.62
	RAa	0.6	0.6	0.61	0.62
	IOb	0.6	0.6	0.6	0.62
	IOa	0.56	0.57	0.61	0.62
	EOb	0.6	0.6	0.6	0.59
	EOa	0.6	0.6	0.61	0.62
	MLb	0.56	0.56	0.62	0.63
	MLa	0.56	0.56	0.66	0.67
	ICb	0.6	0.6	0.6	0.6
	ICa	0.6	0.6	0.7	0.7
Pain-free group	RA	0.48	0.47	0.44	0.52
	IO	0.44	0.4	0.5	0.5
	EO	0.43	0.4	0.33	0.36
	ML	0.52	0.53	0.45	0.41
	IC	0.42	0.4	1	0.95

Groups	Muscle	STS		FRR		FF	
		AUC-LR	AUC-SPSS	AUC-LR	AUC-SPSS	AUC-LR	AUC-SPSS
Stabilization group	RAb	0.42	0.42			-	-
	RAa	0.4	0.4			-	-
	IOb	0.42	0.42			-	-
	IOa	0.4	0.4	0.73	0.3	-	-
	EOb	0.42	0.42	0.5	0.44	-	-
	EOa	0.42	0.42	0.7	0.65	-	-
	MLb	0.43	0.47	0.5	0.5	0.57	0.76
	MLa	0.92	0.75			0.2	0.58
	ICb	0.5	0.53			0.66	0.68
	ICa	0.74	0.66			0.84	0.31
Movement group	RAb	0.58	0.57			-	-
	RAa	0.56	0.6			-	-
	IOb	0.52	0.57			-	-
	IOa	0.56	0.61	0.66	0.67	-	-
	EOb	0.48	0.5	1	0.97	-	-
	EOa	0.52	0.58	0.62	0.64	-	-
	MLb	0.88	0.92	0.62	0.64	0.58	0.64
	MLa	0.63	0.64			0.71	0.65
	ICb	0.88	0.92			0.5	0.48
	ICa	0.6	0.66			0.71	0.65
Pain-free group	RA	0.71	0.7			-	-
	IO	0.6	0.73			-	-
	EO	0.84	0.9	0.85	0.81	-	-
	ML	0.8	0.8	0.6	0.6	0.59	0.66
	IC	0.9	0.8			0.71	0.75



Abbreviations: AUC-LR: Area under curve-logistic regression; AENSLBP: Active extension nonspecific low back pain; RAb: Rectus abdominis before; RAa: Rectus abdominis after; IOb: Internal oblique before; IOa: Internal oblique after; EOb: External oblique before; EOa: External oblique after; MLb: Multifidus before; MLa: Multifidus after; ICb: Iliocostalis before; ICa: Iliocostalis after; FRR: Flexion relaxation ratio; STS: Sit to stand; FF: Forward flexion.

Table S3. Performance parameters of logistic regression supervised machine learning for predicting trunk muscles activity

Muscle Activity; Groups	Muscle	Sensitivity(%)	Specificity(%)	Accuracy (%)	F1-Score
One leg close; Stabilization group	RAb	0.92	1	95	0.96
	RAa	0.93	1	95	0.96
	IOb	0.92	1	95	0.96
	IOa	0.92	1	95	0.96
	EOb	0.92	1	95	0.96
	EOa	0.92	1	95	0.96
	MLb	0.93	1	95	0.96
	MLa	0.96	1	98	0.98
	ICLb	0.93	1	95	0.96
One leg close; Movement group	ICLa	0.93	1	95	0.96
	RAb	0.93	1	95	0.96
	RAa	0.93	1	95	0.96
	IOb	0.92	1	95	0.96
	IOa	0.93	1	95	0.96
	EOb	0.92	1	95	0.96
	EOa	0.93	1	95	0.96
	MLb	0.92	1	95	0.96
	MLa	0.92	1	95	0.96
Double leg close; Pain-free group	ICLb	0.89	1	92	0.94
	ICLa	0.93	1	95	0.96
	Ra	0.4	0.38	40	0.6
	Io	0.41	0.38	40	0.41
	Eo	0.44	0.4	42	0.88
Double leg open; Stabilization group	ML	0.42	0.4	0.55	0.75
	IC	0.46	0.43	0.45	0.5
	RAb	1	1	100	1
	RAa	1	1	100	1
	IOb	1	1	100	1
	IOa	1	1	100	1
	EOb	1	1	100	1
	EOa	1	1	100	1
	MLb	1	1	100	1
Double leg open; Movement group	MLa	1	1	100	1
	ICLb	0.94	1	98	0.97
	ICLa	1	1	100	1
	RAb	0.96	0.92	95	0.96
	RAa	0.96	1	97	0.97
	IOb	0.93	0.92	92	0.96
	IOa	0.93	0.92	92	0.96
	EOb	0.93	0.92	92	0.96
	EOa	0.96	0.92	100	0.96
Double leg open; Pain-free group	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
	ICLa	1	1	100	1
	Ra	0.48	0.46	47	0.5
One leg open; Stabilization group	IO	0.45	0.41	64	0.45
	EO	0.52	0.53	52	0.55
	ML	0.47	0.45	46	0.5
	IC	0.6	0.88	66	0.6
	RAb	1	1	100	1
One leg open; Stabilization group	RAa	1	1	100	1
	IOb	1	1	100	1
	IOa	1	1	100	1
	EOb	1	1	100	1
	EOa	1	1	100	1
	MLb	0.84	1	9	0.91
	MLa	1	1	100	1
	ICLb	0.87	1	93	0.93
	ICLa	1	1	100	1



Muscle Activity; Groups	Muscle	Sensitivity(%)	Specificity(%)	Accuracy (%)	F1-Score
One leg open; Movement group	RAb	0.93	1	95	0.96
	RAa	0.93	1	95	0.96
	IOb	0.92	1	95	0.96
	IOa	0.92	1	95	0.96
	EOb	0.92	1	95	0.96
	EOa	0.93	1	95	0.96
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
One leg open; Pain-free group	ICLa	1	1	100	1
	Ra	0.4	0.38	55	0.4
	Io	0.45	0.42	56	0.46
	Eo	0.53	0.55	53	0.53
	ML	0.46	0.44	45	0.46
FRR; Stabilization group	IC	0.62	0.85	70	0.61
	MLb	0.97	1	98	0.98
	MLa	1	0.88	98	0.98
	ICb	1	0.88	98	0.98
FRR; Movement group	ICa	0.97	1	98	0.98
	MLb	1	0.88	98	0.98
	MLa	0.98	1	98	0.98
	ICb	1	0.88	98	0.99
FRR; Pain-free group	ICa	1	0.88	98	0.98
	ML	0.37	0.35	36	0.4
FF; Stabilization group	IC	0.45	0.42	44	0.45
	MLb	0.94	1	95	0.96
	MLa	1	1	100	1
	ICb	0.94	1	95	0.97
FF; Movement group	ICa	1	1	100	1
	MLb	0.94	1	95	0.97
	MLa	1	1	100	1
	ICb	0.94	1	95	0.97
FF; Pain-free group	ICa	1	1	100	1
	ML	0.49	0.49	50	0.5
STS; Stabilization group	IC	0.72	0.79	75	0.71
	RAb	0.96	0.92	95	0.95
	RAa	0.97	1	97	0.95
	IOb	0.97	0.93	97	0.95
	IOa	0.96	1	97	0.97
	EOb	0.93	0.92	92	0.93
	EOa	0.96	1	97	0.97
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
STS; Movement group	ICLa	1	1	100	1
	RAb	0.96	0.92	95	0.95
	RAa	0.96	1	97	0.97
	IOb	0.93	0.92	92	0.93
	IOa	0.96	1	97	0.97
	EOb	0.93	0.92	92	0.93
	EOa	0.96	1	97	0.97
	MLb	1	1	100	1
	MLa	1	1	100	1
	ICLb	1	1	100	1
STS; Pain-free group	ICLa	1	1	100	1
	RA	0.38	0.37	40	0.4
	IO	0.39	0.36	40	0.38
	EO	0.43	0.41	42	0.43
	ML	0.48	0.47	50	0.46
	IC	0.54	0.57	55	0.54

Abbreviations: RAb: Rectus abdominis before; RAa: Rectus abdominis after; IOb: Internal oblique before; IOa: Internal oblique after; EOb: External oblique before; EOa: External oblique after; MLb: Multifidus before; MLa: Multifidus after; ICb: Iliocostalis before; ICa: Iliocostalis after; FRR: Flexion relaxation ratio; STS: Sit to stand; FF: Forward flexion.

Table S4. Mean error of two software

Muscle Activity; Groups	Muscle	Mean Difference	P	Muscle Activity; Groups	Muscle	Mean Difference	P
One leg close; Stabilization group	RAb	1.56	0.00	One leg open; Stabilization group	RAb	1.54	0.00
	RAa	1	0.06		RAa	0.97	0.03
	IOb	1.19	0.04		IOb	1.51	0.00
	IOa	1.25	0.02		IOa	1.42	0.11
	EOb	1.5	0.41		EOb	1.56	0.00
	EOa	1.33	0.03		EOa	1.2	0.052
	MLb	4.08	0.00		MLb	-0.04	0.92
	MLa	3.94	0.002		MLa	1.64	0.07
	ICb	4.2	0.00		ICb	1.99	0.01
ICa	2.19	0.00	ICa	1.95	0.01		
One leg close; Movement group	RAb	1.85	0.004	One leg open; Movement group	RAb	0.32	0.32
	RAa	1.3	0.02		RAa	0.25	0.14
	IOb	1.7	0.006		IOb	0.55	0.47
	IOa	0.22	0.43		IOa	0.58	0.34
	EOb	1.41	0.01		EOb	-0.14	0.77
	EOa	2.2	0.01		EOa	0.27	0.49
	MLb	2	0.014		MLb	4.52	0.01
	MLa	1.42	0.03		MLa	2.06	0.004
	ICb	1.44	0.016		ICb	1.8	0.005
ICa	2.03	0.023	ICa	0.97	0.005		
One leg close; Pain-free group	RA	2.97	0.06	One leg open; Pain-free group	RA	-1.14	0.04
	IO	1.05	0.17		IO	-4.02	0.09
	EO	7.08	0.00		EO	-1.6	0.25
	ML	2.08	0.15		ML	-0.58	0.64
	IC	4.33	0.04		IC	-0.35	0.53
FRR; Stabilization group	MLb	-0.09	0.00	FRR; Pain-free group	ML	0.01	0.08
	MLa	-0.02	0.00		IC	0.00	0.59
	ICb	-0.07	0.00				
	ICa	-0.02	0.00				
FRR; Movement group	MLb	-0.02	0.00	FRR; Stabilization group	MLb	-0.09	0.00
	MLa	-0.003	0.82		MLa	-0.02	0.00
	ICb	-0.02	0.00		ICb	-0.07	0.00
	ICa	-0.009	0.00		ICa	-0.02	0.00
FRR; Pain-free group	ML	0.01	0.08	FRR; Movement group	MLb	-0.02	0.00
	IC	0.00	0.59		MLa	-0.003	0.82
					ICb	-0.02	0.00
					ICa	-0.009	0.00
FF; Stabilization group				STS; Stabilization group	RAb	0.95	0.00
					RAa	0.41	0.00
					IOb	0.59	0.00
					IOa	0.21	0.00
					EOb	0.47	0.00
					EOa	0.37	0.00
					MLb	2.5	0.00
			MLa	1.41	0.00		
			ICb	2.7	0.00		
			ICa	3.5	0.00		
FF; Movement group				STS; Movement group	RAb	-0.17	0.54
					RAa	-0.04	0.67
					IOb	-0.5	0.00
					IOa	-0.7	0.14
					EOb	-0.45	0.00
					EOa	-0.23	0.26
					MLb	0.3	0.43
			MLa	1.42	0.1		
			ICb	0.4	0.38		
			ICa	0.36	0.36		
FF; Pain-free group				STS; Pain-free group	RA	-0.61	0.32
					IO	-0.26	0.45
					EO	-1	0.00
					ML	0.09	0.91
				IC	0.04	0.94	

Abbreviations: RAb: Rectus abdominis before; RAa: Rectus abdominis after; IOb: Internal oblique before; IOa: Internal oblique after; EOb: External oblique before; EOa: External oblique after; MLb: Multifidus before; MLa: Multifidus after; ICb: Iliocostalis before; ICa: Iliocostalis after; FRR: Flexion relaxation ratio; STS: Sit to stand.