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Clustering of pelvic-supporting muscles activity in individuals with Lumbar Hyperlordosis in stance phase of walking: a machine learning approach

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ABSTRACT

Background: Lumbar Hyperlordosis (LH) is associated with lumbar muscle defects or altered muscle engagement patterns, leading to low back pain. However, the specific muscle most influential in causing this condition remains unclear. This study aims to determine effective prescient alternative to Lumbar Hyperlordosis (LH) from muscular activity variables in stance phase of walking, in addition to discovering homogenous clusters of individuals based on the primary predictive alternative.
Methods: The activity of Rectus Femoris (RF), Gluteus Medius (GM), and Lumbar Erector Spinae (LES) was recorded in 40 females suffering from LH while walking. Maximum activity and muscular involvement for each muscle were extracted. A multilayer perceptron artificial neural network was used to detect notable projected variables of LH. K-means clustering was then employed to identify homogeneous clusters of individuals based on the most significant predictive variable. The One-Way ANOVA test used to identify homogenous clusters.
Results: The results demonstrated that RF maximum activity with an accuracy of 90.9%, was detected as the most prominent predictive variable. The One-Way ANOVA test demonstrated significant differences among the three homogeneous clusters of individuals based on Rectus Femoris maximum activity ($P \leq 0.05$).
Conclusions: The classification scheme presented in this paper can describe muscle activity patterns while walking and may be useful for screening individuals suffering from Lumbar Hyperlordosis and for clinical decision-making based on clusters. The maximum activity of the Rectus Femoris is the most important factor affecting lumbar hyperlordosis, which is relevant in rehabilitation and health fields.

KEYWORDS
Gait, Lumbar Hyperlordosis, Machine learning, Pelvic-supporting muscles.

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Introduction

Lumbar hyperlordosis (LH), characterized by increased lumbar curvature, results from anterior pelvic tilt and hip flexion[1]. This condition is a leading cause of low back pain globally, particularly affecting women[2], and impacts daily activities such as walking [3], leading to chronic low back pain during walking and standing [4]. LH is associated with Pelvic Crossed Syndrome where the erector spinae muscles and hip flexors become tight while gluteal muscles weaken[5]. This muscular imbalance disrupts the lumbopelvic rhythm and impairs pelvic function[6]. The stability of the lumbo-pelvic belt is compromised without the proper functioning of the pelvic supporting muscles[7].

The association between LH and shortness of rectus femoris, lumbar erector spinae[2, 8] and decreased activity of the gluteus medius was showen during walking, single leg squat and landing [6].

Recent studies suggest that individuals exhibiting with similar muscle activity patterns may respond similarly to therapeutic interventions. Machine learning(ML) techniques particularly artificial neural networks (ANN), have been effectively employed to predict gait events and identify significant predictive variables related to spinal abnormalities and low back pain[9,14].

Saranya et al. have highlighted the suitability of lumbar erector spinae muscles for predicting chronic low back pain[10]. Additionally, Piatkowska et al. reported the thigh and leg muscles are appropriate for clustering diabetic patients during walking and climbing the stairs [11]. ML and deep learning have also proven effective in interpreting surface electromyography (sEMG) signals for various applications, including gesture classification and muscle fatigue detection, Different models were adopted: convolutional and recurrent neural networks for muscle force estimation and multi-layer perceptron to classify neuromuscular disorders, applied to the sEMG signal for classification purposes and for the detection of physiological patterns and parameters[12]. And also according to the background of studies Clustering methods has also used for detect agonist and antagonist muscles activity patterns of leg during gate based on hierarchical and k-means techniques in healthy people[13, 14]. Despite the advances in ML applications, there is limited research on the evaluation of posture parameters and abnormalities like hyperlordosis and hyperkyphosis[12]. This raises the question of whether muscle activity patterns during walking can effectively predict and cluster individuals with lumbar hyperlordosis. Hence, a machine learning approach tested in this study to assess activity of three muscles with different role and placement areas (rectus femoris in the anterior part of body as a hip flexor, lumbar erector spinae in the posterior area as a trunk extensor and gluteus medius in the external side as a supportive muscle) to find which of them predict LH better in walking[6, 15] because it has been stated that the most effective variable in generating homogeneous clusters may be helpful in developing specific prescriptions for patients[16]. According to our knowledge Probably machine learning methods are helpful in finding homogeneous clusters of patients with lumbar hyperlordosis with similar patterns of muscle activity in the support phase of gait. Therefore, the first objective of the present study is to find the most important variables in predicting lumbar hyperlordosis using variables with maximum activity and the novelty of this work is in the use of multilayer perceptron (MLP) to a spinal dataset to obtain high accuracy in spinal abnormality detection. The second objective is to find homogeneous clusters based on muscle activity patterns using K-means clustering. Identifying the most effective variables for generating homogeneous clusters could aid in developing specific prescriptions for patients.

Material and Methods

Participants

The study population consisted of female students aged 20 to 35 years with HL of Shahid Beheshti University. Forty participants as available according to the background of studies[17] (age: 27±3.87 years, height: 160±5.48 cm, mass: 63±10.91 kg, bmi: 25±3.94 kg/m^2, lumbar lordosis 49±12.74 degrees) voluntarily participated. The inclusion criteria included no history of spinal surgery, absence of spinal and lower extremity structural abnormalities, no back pain, non-pregnancy, no childbirth in the last six months, and a BMI of 23-28 kg/m^2. And Non-cooperation until the end of the implementation of the protocol was considered as an exclusion criteria. This study was conducted in the Laboratory of Sports sciences and Wellbeing at Shahid Beheshti University, adhering to the ethics code IR.SBU.REC.1400.230. Researchers evaluated spinal cord abnormalities in participants using a checkered board alongside a demographics questionnaire. Participants with lumbar hyperlordosis exceeding the normal range of 30 degrees were selected for the study[4]. Comprehensive information regarding the research process was provided to all participants to ensure informed consent and understanding of the study's objectives.

Instruments

The lumbar angle was measured using a flexible ruler based on the Youdas method[2]. For the lumbar curvature test, participants were positioned in a natural upright barefoot position. The T12 and S2 Vertebrae were marked. The flexible ruler was placed on the skin while applying appropriate pressure. The distance between the two marked points was then plotted on paper without any alterations[18]. The lordosis angle (θ) was calculated using the following formula: [19]:

$$\text{Equation 1: } \theta = 4[\text{Arctan}\frac{2H}{L}]$$

Where θ is the lordosis angle, and L and H represent the length and height of the curve, respectively.

To record EMG activity of the Rectus Femoris (RF) and Lumbar Erector Spinae (LES) (with agonist and antagonist role in stability of lumbopelvic region) and Gluteus Medius (GM) (hip abductor and stablilizer of pelvis during walking)[5, 15], the dominant leg was chosen for matching subjects because for starting nature tasks like walking most subjects will use the dominant leg[20]. A 16-channel ME6000 system was utilized with a 16-bit A/D converter and a sampling frequency of 1000 Hz (Mega Electronics, Finland). Bipolar electrodes containing conductive gel and adhesive were attached to the skin with a center-to-center distance of 2 cm between electrodes. A foot scanner was employed to synchronously identify the time interval between heel strikes and toe lifts, accurately detecting stance phase events during walking.

Data collection

After skin preparation with shaving and using alcohol, surface electrodes were placed on desired muscles following SENIAM recommendations[21]. Each participant's maximum voluntary isometric activity was recorded prior to walking trials. Participants walked along a 12-meter walkway at their preferred speed, and data from the seventh stride was analyzed[22]. Walking speed was calculated by dividing the walking distance by the walking time[23]. Trials were considered valid for analysis starting from the third stride onward. The recorded data from the stance phase of the seventh step is illustrated in Figure 1.

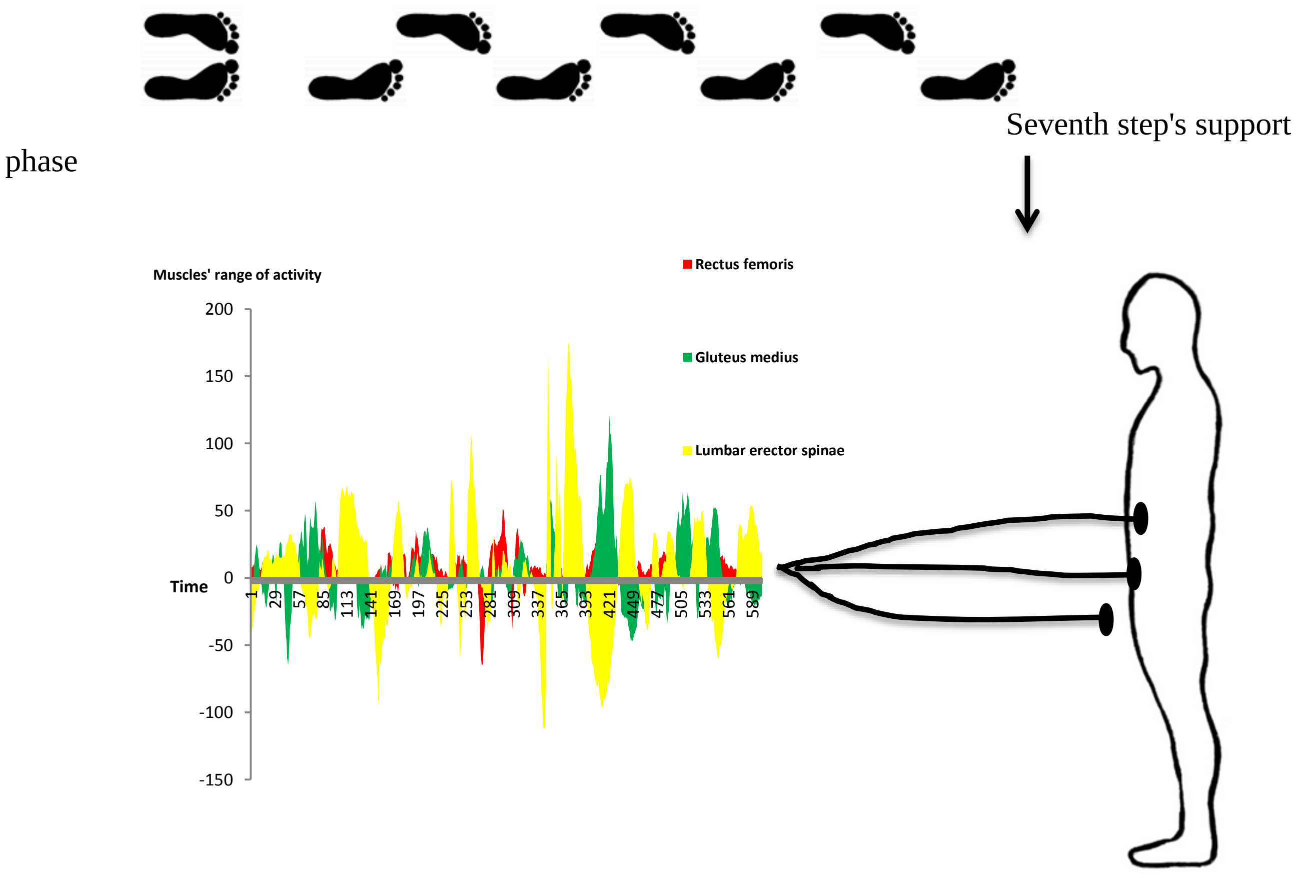

Figure 1. Recorded data of the support phase of the seventh step

Preprocessing

A band-pass filter was applied with cutoff frequencies of 10 to 480 Hz to eliminate noise from the raw EMG data in MATLAB software (version a2014). The linear envelope process was applied by a full rectification and a 20 Hz low pass filter to smooth the rectified signal[24]. The electromyographic activity of the muscles was normalized based on the maximum value obtained from the Maximum Voluntary Isometric Contraction (MVIC) test.

The muscle co-contraction variable was calculated using the Equation 2[25].

$$\text{Equation 2: co-contraction} = 2\times \left(\frac{Common\ Area\ A\ \&\ B}{Area\ A + Area\ B}\right) \times 100$$

Area A was defined as the area under the EMG curve of muscle A, and area B as the area under the curve of muscle B in Figure 3. Also the common area A&B was defined as the overlapping area between muscle A and muscle B on the mean EMG curve.

Statistical analysis

The muscle co-contraction and maximum activity variables were analyzed using SPSS software (version 22). The most important predictor of lumbar hyperlordosis was identified using a Multilayer-Perceptron Neural Network[26]. This method as an ANN applies a unit (neuron) whose output is a nonlinear differentiable function of its input[27]. MLP employs the supervised learning Backpropagation (BP) algorithm for network training and the gradient descent weight update rule for computing new weights during the learning process[28, 30].

In this work, the MLP comprised of three layers. The input layer in MLP artificial neural network can be mathematically described as follows[29]:

Equation 3: Input layer: jo = P units, a0;1,…,a0:jo;with
a0:jo= xj,

where j is the number of neurons in the layer and X is the input.
The neural network was trained to differentiate between the two classes of lordosis angles based on the input variables (muscle co-contraction and maximum muscle activity). This classification aimed to identify patterns and predictors associated with varying degrees of lumbar hyperlordosis (class 1 = 30 to 40 degrees and class 2 = greater than 40 degrees). To avoid overfitting, 72.5% (29 people) of the participants were used for training, and 27.5% (11 people) were used to test the neural network. The data was validated five times to achieve the best network type with the minimum errors[31]. The generated neural network is presented in Figure 2.

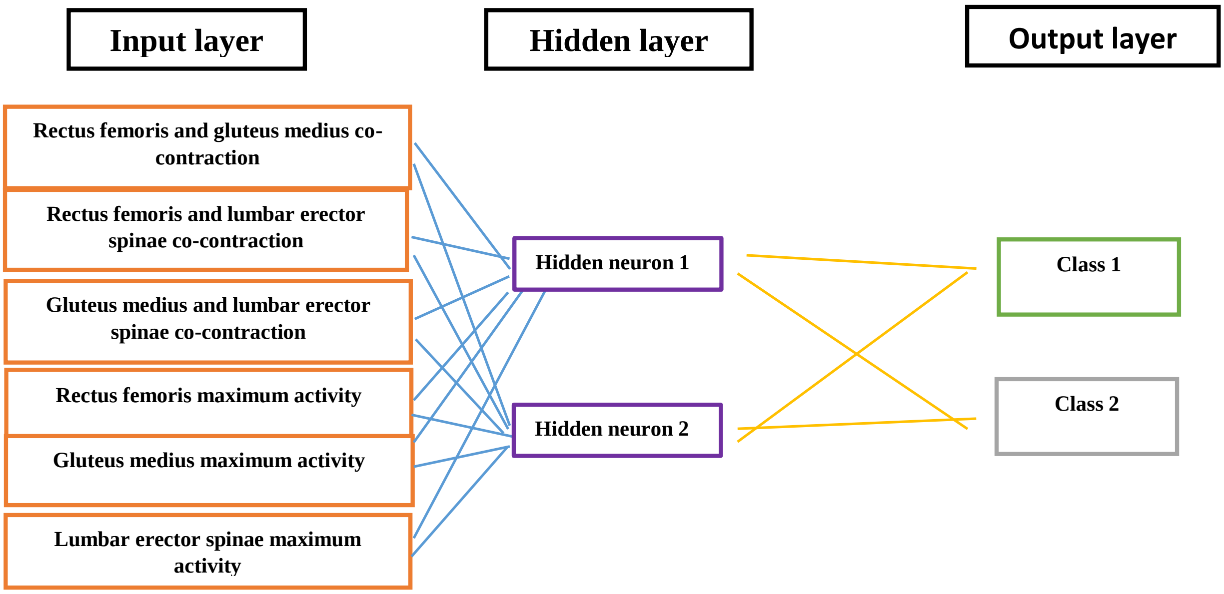

Figure 2. The three-layered neural network based on the co-contraction and maximum activity of Rectus femoris, Gluteus medius, Lumbar Erector-spinae.

The clustering of people was done according to the most important predictor using the K-means clustering method. The algorithm's goal in this clustering method is to reduce the sum of the squared error over all k clusters. The objective function to minimize is[28]:

$$\text{Equation 3: } J = \sum_{j=1} k \sum_{i=1} n \ \left\| x_i^{(i)} - \mathrm{cj}^2 \right\|,$$

Where: i = 1, …, n; , n is the data points to be clustered into k clusters and C = {cj, j = 1, …, K} is the cluster center.
To identify the most appropriate number of clusters, 2 to 5 clusters were formed[32]. Convergence achieved due to or no small change in cluster centers. The maximum absolute coordinate change for any center is 0.000. Shapiro-wilk test was used for normality and a one-way ANOVA test to investigate the intergroup variance[33].

Results

The muscle co-contraction variable for each three muscles was visually presented in Figure3. The results of the artificial neural network indicated that the maximum activity of the Rectus Femoris was the most effective predictor of LH. K-means clustering revealed three homogeneous clusters of individuals based on muscle activity patterns.

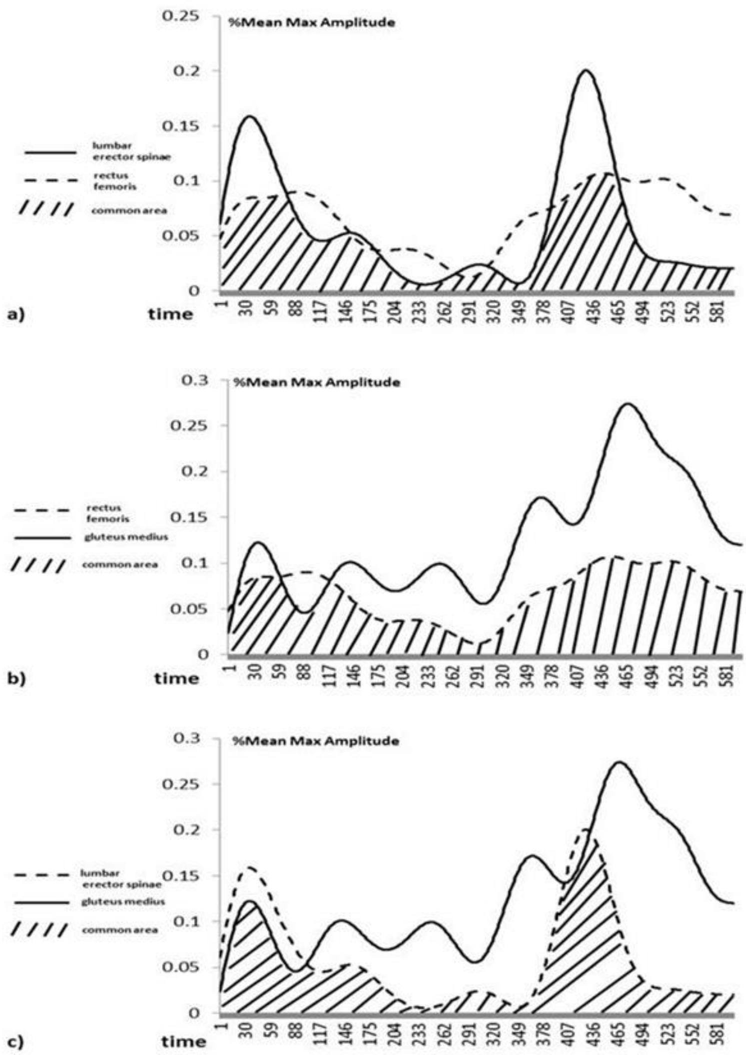

Figure3. Evaluation of muscles' co-contraction. a) co-contraction of lumbar erector spinae and rectus femoris. b) co-contrction of rectus femoris and gluteus medius. c) co-contrction of lumbar erector spinae and gluteus medius.

Results of the artificial neural network

The results of training five different neural networks were analyzed to determine the highest prediction accuracy and the lowest errors, as presented in Table 1 below.

Table 1. Accuracy and error percentage of the prediction of the neural networks

The most important predictive variable	Clustering accuracy percentage in the test group	Clustering accuracy percentage in the training group	Error percentage in the test group	Error percentage in the training group	Neural network
Rectus femoris and lumbar erector spinae co-contraction	56.3	79.2	43.8	20.8	First
Rectus femoris maximum activity	90.9	89.7	9.1	10.3	Second
Gluteus medius and lumbar erector spinae co-contraction	69.2	74.1	30.8	25.9	Third
Gluteus medius and lumbar	80	60	20	40	Fourth

erector spinae co-contraction					
Gluteus medius and lumbar erector spinae co-contraction	69.2	77.8	30.8	22.2	Fifth

As presented in Table 1, the second network achieved a prediction accuracy of 90.9% in the test group clustering, making it the best fit network for this analysis. The results from this network were utilized for the clustering process.

Figure 4 illustrates the effectiveness percentage of each predictor variable related to lumbar hyperlordosis in the second neural network. The analysis indicates that The maximum activity of the rectus femoris is the most effective variable in predicting lumbar hyperlordosis, Other muscle activity variables show lower effectiveness percentages, indicating that they are less significant in the predictive model for lumbar hyperlordosis.

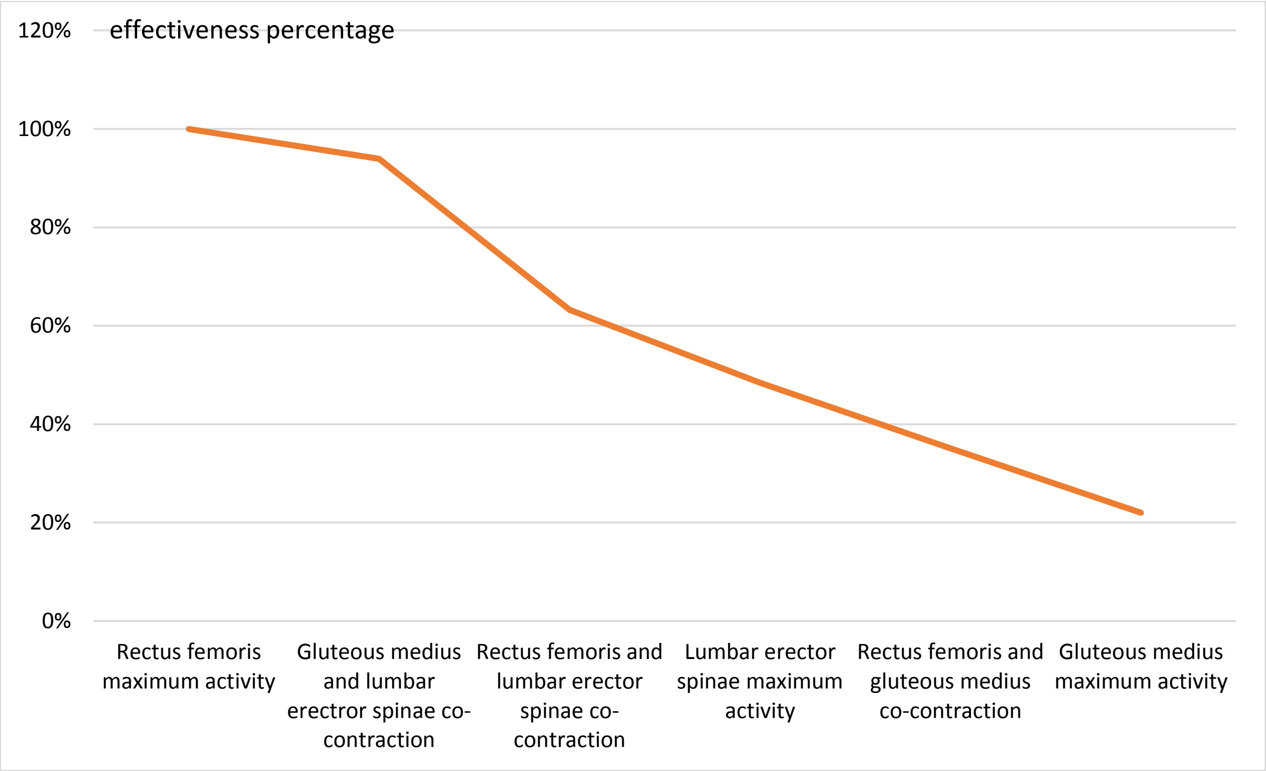

Figure 4. The effectiveness percentage of muscle activity variable

Results of K-means

According to Figure 4, the maximum activity of the rectus femoris is identified as the most crucial variable for predicting lumbar hyperlordosis. It appears that the maximum activity of the rectus femoris tends to predict lumbar hyperlordosis more effectively than other muscle activity variables. In the present study, participants were clustered according to their muscle activity patterns, specifically focusing on the maximum activity of the rectus femoris.

To determine the best clustering type for the study, the results of the one-way ANOVA revealed a significant difference between all groups within the clusters only with 3 clusters ($P \leq 0.05$). Table2 presents the results of this test. Furthermore, when considering three clusters, the convergence between the data and the cluster center is achieved faster and completed with two clustering repetitions. At the same time, the number of repetitions reached 6, considering the other number of clusters. Table 3 presents the converging results.

Table2. ANOVA result for 3 clusters

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Maximum of Rectus femoris	2.549	2	.017	37	150.750	.000

Table 3. History of layer-building repetitions

Repetition	Mean change of the difference between data and center of the clusters		
	1	2	3
1	0.079	0.073	0.185
2	0.000	0.000	0.000

Clustering participants of the present study into three clusters resulted in clusters of 30, 8, and 2 participants, which are presented based on the angle of lumbar hyperlordosis and maximum activity of the rectus femoris with greatest importance in predicting LH in Figures 5 and 6, respectively. As shown in this table, 8 participants are in the first cluster, 2 in the second cluster, and 30 in the third cluster.

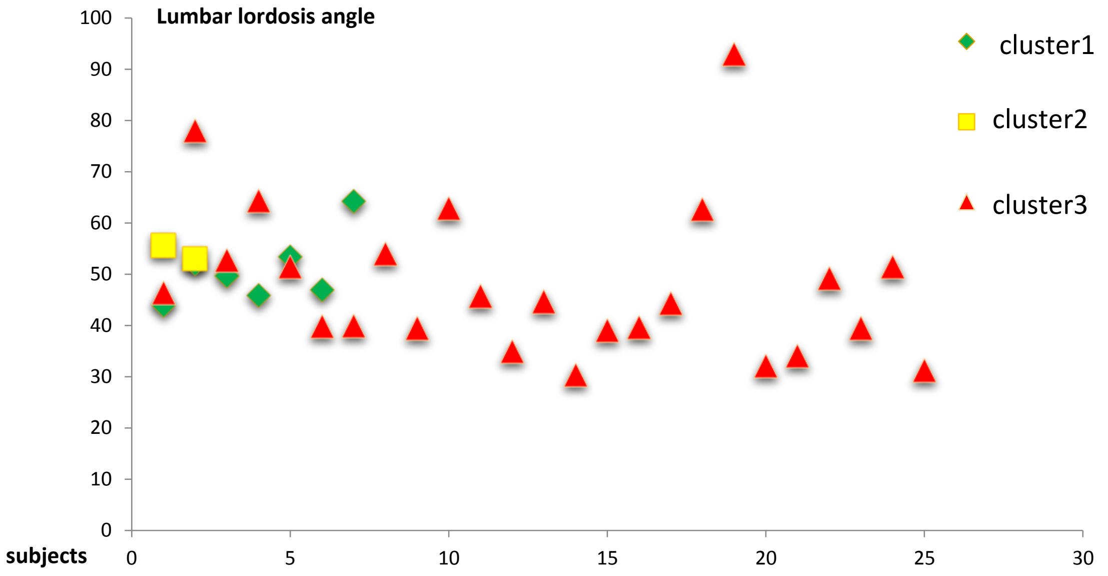

Figure 5. Clusters based on the lumbar lordosis angle

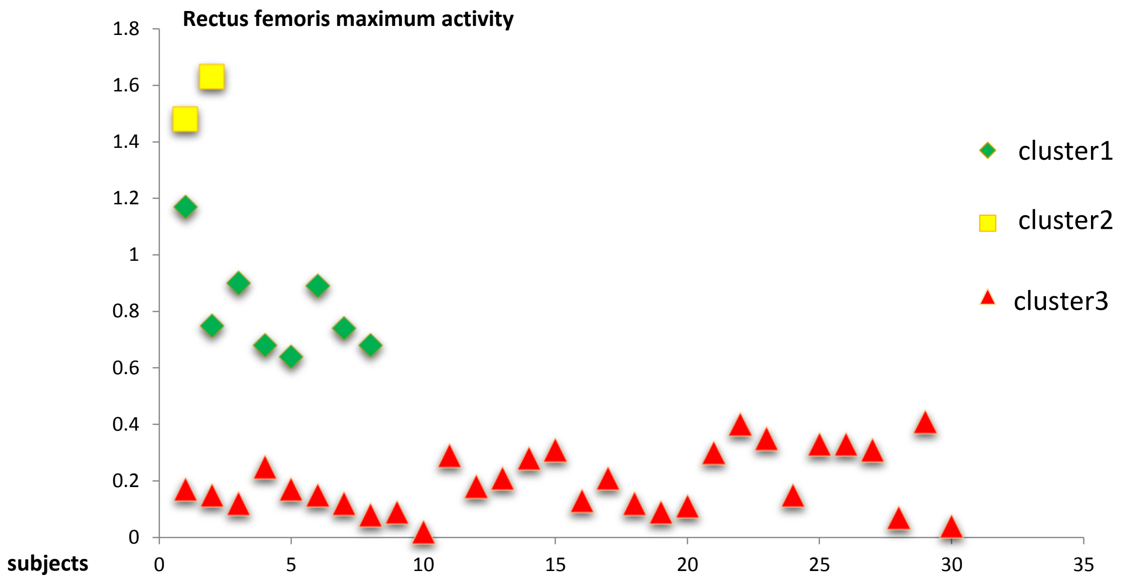

Figure 6. Clusters based on rectus femoris maximum activity

Participants in the second cluster exhibit similar levels of lordosis angle as those in the other clusters; however, they are categorized separately due to a significantly increased maximum activity of the rectus femoris. Additionally, participants in the first cluster demonstrate higher maximum activity of the rectus femoris compared to those in the third cluster.

Discussion

The present study aimed to identifying the most effective muscle predicting lumbar hyperlordosis during walking with testing the ability of Multilayer-Perceptron neural networks. Additionally, lumbar hyperlordosis was clustered using a machine learning algorithm based on the most effective muscle activity variable. These algorithms discover hidden patterns in data without the need for human intervention[18]. In this study, five independent Multilayer-Perceptron neural networks were created and compared; the second model exhibited a lower error rate (9.1%) compared with the others (with the prediction accuracy of 90.9%) and was deemed the best network. Most studies consider neural networks with an accuracy of 90% or higher to be suitable. Machine learning approaches collect information from entire time series steps, as opposed to peak or average picking methods[34]. It is believed that considering a limited number of variables may not lead to appropriate clustering or may result in very small clusters, illustrating the complexity and diversity of muscle activity variables[11]. Hence, for more accurate clustering, an artificial neural network was tested in this study to determine which pattern of muscle activity affects lumbar hyperlordosis and can be predicted using artificial neural networks (ANNs). We extended those findings here demonstrate that the predictive capabilities of ANNs are retained during walking, allowing for the identification of the most important features of EMG patterns related to lumbar hyperlordosis and the development of an accurate model for predicting LH. In the next step, k-means clustering was applied based on the most effective feaure to find homogeneous groups of individuals with LH, facilitating the provision of specific modalities. The results of clustering based on key predictor variables obtained from the neural network revealed three homogeneous groups of individuals.

Recently, the predictive use of neural networks has gained popularity in gait research, being utilized to predict spinal abnormalities[35], in addition to studying electrical muscle activity during the gait phase [17, 36, 37]. A study by Kristen Morbidoni et al. predicted foot contact signals from electromyographic signals of leg and thigh muscles, achieving an accuracy of 94.9% using multilayer perceptron neural networks[36]. Another study proposed an artificial neural network to predict gait phases with an accuracy of 87.5% using five time-dependent muscle activity variables[37]. Zahid Rao et al. demonstrated the use of EMG for predicting outcomes in individuals with impaired trunk control, achieving an accuracy of 95.44%[38] supporting our assertion regarding the suitability of machine learning for predicting alignment disorders. Gundala Jhansi Rani et al. employed machine learning technique to detect knee abnormalities based on EMG signals, achieving good accuracy and indicating that predicting abnormalities based on muscle activity is suitable[39] aligning with our results regarding the effectiveness of ML techniques based on EMG.

In addition to presenting our ANN model for prediciting LH based on muscle patterns, we found that the maximum activity of the Rectus Femoris is the most effective feature for predicting LH. This emphasizes the relationship between the Rectus Femoris as a hip flexor and lumbar hyperlordosis during daily activites, which is crucial for rehabilitation[40-42].

Examining the results of K-means clustering according to the maximum activity of Rectus Femoris, a one-way ANOVA test showed significant differences between clusters. Notably, the lordosis angle of one cluster was similar to that of the other groups, although they differed regarding the maximum activity of the Rectus Femoris during the stance phase of gait. The study by Izadi Farhadi et al.'s indicated increased activity of the Rectus Femoris and Gluteus Maximus in individuals with lumbar hyperlordosis compared to healthy individuals[6], which is consistent with our findings. A study by Ruixin Liang et al. (2022) tested paraspinal muscle activity patterns in patients with scoliosis and identified homogeneous clusters of individuals[43]. Using K-NN and K-Means methods to cluster the activity patterns of six basic hand gestures, Erhan-Bargil et al. reported higher accuracy for the second method[44]. Clustering of muscle activity patterns in patients with hemophilia, cerebral palsy, and diabetes revealed homogenous clusters of patients[22, 32, 45]. Utilizing muscle activity features likely provides a framework for classifying individuals during walking.

The three clusters of individuals with lumbar hyperlordosis differentiate themselves by more than just lordosis angles, highlighting the importance of muscle activity for clustering. This new classification scheme can effectively describe muscle activity patterns while walking. Furthermore, the findings of this study align with research that identified the Rectus Femoris as a suitable muscle for clustering patients with low back pain , indicative of LH[45] and may assist in clinical decision-making differentiation of patients with lumbar hyperlordosis[46]. Overall, the results of the machine learning model developed in this study suggest that our model is sutiable for predicting individuals with LH based on EMG signals, facilitating their clustering and providing valuable insights for clinical applications.

Conclusion

This study provides valuable insights into the application of machine learning techniques for analyzing EMG patterns in women with lumbar hyperlordosis (LH), potentially informing the development of more efective treatments. The results indicate that our machine learning (ML) model is suitable for predicting lumbar hyperlordosis abnormalities based on muscle activity. This allows therapists to anticipate LH abnormalities in individuals based on muscle patterns. Notably, the maximum activity of the Rectus Femoris was identified as the most significant factor affecting LH. This finding suggests that clustering patients with hyperlordosis based on muscle activity, rather than solely relying on LH angles, may yield more relevant insights in rehabilitation and health fields, facilitating the identification of homogeneous groups. Considering the associated variables to muscle activity and the impact of participant numbers on the efficacy of the employed approach, it is recommended that future studies take these factors into account. We advocate for the adoption of machine learning as an essential tool for predicting abnormalities, which may enhance clinical decision-making and improve patient outcomes.

Ethical Considerations:

Compliance with ethical guidelines

We state that all authors have made substantial contributions to all of the following: (1) the conception and design of the study, or acquisition of data, or analysis and interpretation of data, (2) drafting the article or revising it critically for important intellectual content, (3) final approval of the version to be submitted.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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References

1. Alizadeh, M. and M. Gheitasi, Fundamental Concepts of Corrective Exercises. 3st Publish. Sport Science Research Center, 2019. 23(2): p. 148-163.

2. Janyathitipath, T., et al., Responsiveness of Lumbar Lordosis Angle and Other Biomechanical Parameters in Individuals with Lumbar Hyperlordosis: An Experimental Study. Srinagarind Medical Journal, 2020. 35(4): p. 470-475.

3. Scannell, J.P. and S.M. McGill, Lumbar posture—should it, and can it, be modified? A study of passive tissue stiffness and lumbar position during activities of daily living. Physical Therapy, 2003. 83(10): p. 907-917. https://doi.org/10.1093/ptj/83.10.907

4. Been, E. and L. Kalichman, Lumbar lordosis. The Spine Journal, 2014. 14(1): p. 87-97. 10.1016/j.spinee.2013.07.464

5. Clark, M. and S. Lucett, NASM essentials of corrective exercise training. 2010: Lippincott Williams & Wilkins. 0781768020, 9780781768023

6. Farhadi, M.H.I., et al., Differences in Gluteal and Quadriceps Muscle Activation Among Adults With and Without Lumbar Hyperlordosis. Journal of sport rehabilitation, 2020. 29(8): p. 1100-1105. 10.1123/jsr.2019-0112

7. Fatemi, R., M. Javid, and E.M. Najafabadi, Effects of William training on lumbosacral muscles function, lumbar curve and pain. Journal of back and musculoskeletal rehabilitation, 2015. 28(3): p. 591-597. 10.3233/BMR-150585

8. Youdas, J.W., et al., Lumbar lordosis and pelvic inclination in adults with chronic low back pain. Physical therapy, 2000. 80(3): p. 261-275. 10696153https://doi.org/10.1093/ptj/80.3.261

9. Jiang, N., K.D.-K. Luk, and Y. Hu, A machine learning-based surface electromyography topography evaluation for prognostic prediction of functional restoration rehabilitation in chronic low back pain. Spine, 2017. 42(21): p. 1635-1642. 10.1097/BRS.0000000000002159

10. Saranya, S., et al., EMG Features as an Indicator of Muscle Strength for the Assessment of Non-Specific Low Back Pain, in Assistive Technology Intervention in Healthcare. 2022, CRC Press. p. 177-188. 9781003207856

11. Piatkowska, W., et al., EMG analysis across different tasks improves prevention screenings in diabetes: a cluster analysis approach. Medical & biological engineering & computing, 2022. 60(6): p. 1659-1673. https://doi.org/10.1016/j.gaitpost.2020.08.031

12. Di Nardo, F., et al., Machine learning for detection of muscular activity from surface EMG signals. Sensors, 2022. 22(9): p. 3393. https://doi.org/10.3390/s22093393

13. Rosati, S., et al., Muscle activation patterns during gait: A hierarchical clustering analysis. Biomedical Signal Processing and Control, 2017. 31: p. 463-469. https://doi.org/10.1016/j.bspc.2016.09.017

14. White, S.G. and P.J. McNair, Abdominal and erector spinae muscle activity during gait: the use of cluster analysis to identify patterns of activity. Clinical Biomechanics, 2002. 17(3): p. 177-184. https://doi.org/10.1016/S0268-0033(02)00007-4

15. Hodges, P.W. and C.A. Richardson, Inefficient muscular stabilization of the lumbar spine associated with low back pain: a motor control evaluation of transversus abdominis. Spine, 1996. 21(22): p. 2640-2650.

16. D'Antoni, F., et al., Artificial Intelligence and Computer Aided Diagnosis in Chronic Low Back Pain: A Systematic Review. International Journal of Environmental Research and Public Health, 2022. 19(10): p. 5971. https://doi.org/10.3390/ijerph19105971

17. Nazmi, N., et al., Walking gait event detection based on electromyography signals using artificial neural network. Biomedical Signal Processing and Control, 2019. 47: p. 334-343. https://doi.org/10.1016/j.bspc.2018.08.030

18. Youdas, J.W., J.H. Hollman, and D.A. Krause, The effects of gender, age, and body mass index on standing lumbar curvature in persons without current low back pain. Physiotherapy theory and practice, 2006. 22(5): p. 229-237. https://doi.org/10.1080/09593980600927864

19. Puntumetakul, R., et al., The relationships between gender body mass index and lumbar spinal curvature in standing position using the flexible ruler. Journal of Medical Technology and Physical Therapy, 2001. 13(1): p. 20-29. https://doi.org/10.14456/arch-ahs

20. Bhise, S.A. and N.K. Patil, Dominant and non-dominant leg activities in young adults. International Journal of Therapies and Rehabilitation Research, 2016. 5(4): p. 257-64. https://doi:10.5455/ijtrr.000000172

21. Hermens, H.J., et al., Development of recommendations for SEMG sensors and sensor placement procedures. Journal of electromyography and Kinesiology, 2000. 10(5): p. 361-374. https://doi.org/10.1016/S1050-6411(00)00027-4

22. Cruz-Montecinos, C., et al., Changes in muscle activity patterns and joint kinematics during gait in hemophilic arthropathy. Frontiers in physiology, 2020. 10: p. 1575. https://doi: 10.1088/0967-3334/34/8/N63

23. Tirosh, O. and W. Sparrow, Age and walking speed effects on muscle recruitment in gait termination. Gait & Posture, 2005. 21(3): p. 279-288. https://doi.org/10.1016/j.gaitpost.2004.03.002

24. Balbinot, A. and G. Favieiro, A neuro-fuzzy system for characterization of arm movements. Sensors, 2013. 13(2): p. 2613-2630. https://doi.org/10.3390/s130202613

25. Wayne, P.M., et al., Tai chi training's effect on lower extremity muscle co-contraction during single-and dual-task gait: cross-sectional and randomized trial studies. PloS one, 2021. 16(1): p. e0242963. https://doi.org/10.1371/journal.pone.0242963

26. Elamvazuthi, I., et al., Electromyography (EMG) based classification of neuromuscular disorders using multi-layer perceptron. Procedia Computer Science, 2015. 76: p. 223-228. https://doi.org/10.1016/j.procs.2015.12.346

27. Agatonovic-Kustrin, S. and R. Beresford, Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. Journal of pharmaceutical and biomedical analysis, 2000. 22(5): p. 717-727. https://doi.org/10.1016/S0731-7085(99)00272-1

28. Khong, L.M., et al. Multi-layer perceptron training algorithms for pattern recognition of myoelectric signals. in The 6th 2013 Biomedical Engineering International Conference. 2013. IEEE. https://doi.org/10.1109/BMEiCon.2013.6687665

29. Majidzadeh Gorjani, O., et al., Human activity classification using multilayer perceptron. Sensors, 2021. 21(18): p. 6207. https://doi.org/10.3390/s21186207

30. Yang, J. and G. Yang, Modified convolutional neural network based on dropout and the stochastic gradient descent optimizer. Algorithms, 2018. 11(3): p. 28. https://doi.org/10.3390/a11030028

31. Ying, X. An overview of overfitting and its solutions. in Journal of physics: Conference series. 2019. IOP Publishing. https://doi.org/10.1088/1742-6596/1168/2/022022

32. Sawacha, Z., et al., A new classification of diabetic gait pattern based on cluster analysis of biomechanical data. 2010, SAGE Publications Sage CA: Los Angeles, CA. https://doi.org/10.1177/193229681000400511

33. Harb, H., A. Makhoul, and R. Couturier, An enhanced K-means and ANOVA-based clustering approach for similarity aggregation in underwater wireless sensor networks. IEEE Sensors Journal, 2015. 15(10): p. 5483-5493. 10.1109/JSEN.2015.2443380

34. Kobayashi, Y., et al., Key joint kinematic characteristics of the gait of fallers identified by principal component analysis. Journal of biomechanics, 2014. 47(10): p. 2424-2429. https://doi.org/10.1016/j.jbiomech.2014.04.011

35. Wang, Y., et al. Neural network using for prediction spinal diseases. in Conference of Open Innovations Association, FRUCT. 2019. FRUCT Oy. ISSN 2305-7254

36. Morbidoni, C., et al., A deep learning approach to EMG-based classification of gait phases during level ground walking. Electronics, 2019. 8(8): p. 894. https://doi.org/10.3390/electronics8080894

37. Nazmi, N., et al. Generalization of ANN model in classifying stance and swing phases of gait using EMG signals. in 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES). 2018. IEEE. DOI:10.1109/IECBES.2018.8626626

38. Rao, A.Z., et al., Sensor fusion and machine learning for seated movement detection with trunk orthosis. IEEE Access, 2024. 12: p. 41676-41687. **DOI:** 10.1109/ACCESS.2024.3377111

39. Rani, G.J. and M.F. Hashmi. Electromyography (EMG) Signal based Knee Abnormality Prediction using XGBoost Machine Learning Algorithm. in 2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA). 2023. IEEE. DOI:10.1109/ICIDeA59866.2023.10295245

40. Hudson, K.R., The relationship of hip flexor muscle length to lumbar lordosis and pelvic tilt. 1992: Touro College. DOI: 10.1093/ptj/67.4.512

41. Rhee, I., et al., Hip-spine syndrome in patients with spinal cord injuries: hyperlordosis associated with severe hip flexion contracture. Frontiers in Pediatrics, 2021. 9: p. 646107. https://doi.org/10.3389/fped.2021.646107

42. Seidi, F., et al., Lower limb muscle activation pattern in male soccer players with lumbar hyperlordosis. Journal of Bodywork and Movement Therapies, 2023. 36: p. 263-269. https://doi.org/10.1016/j.jbmt.2023.03.004

43. Liang, R., et al., Electromyographic Analysis of Paraspinal Muscles of Scoliosis Patients Using Machine Learning Approaches. International Journal of Environmental Research and Public Health, 2022. 19(3): p. 1177. https://doi.org/10.3390/ijerph19031177

44. Bergil, E., C. Oral, and E.U. Ergul, Efficient Hand Movement Detection Using k-Means Clustering and k-Nearest Neighbor Algorithms. Journal of Medical and Biological Engineering, 2021. 41: p. 11-24. https://doi.org/10.1007/s40846-020-00537-4

45. Rozumalski, A. and M.H. Schwartz, Crouch gait patterns defined using k-means cluster analysis are related to underlying clinical pathology. Gait & posture, 2009. 30(2): p. 155-160. https://doi.org/10.1016/j.gaitpost.2009.05.010

46. Yousefi, M.and E.A.H, Reliability of Body Landmark Analyzer (BLA) system for Measuring Hyperkyphosis and Hyperlordosis Abnormalities. Journal of Advanced Sport Technology 4(1):20- 29.

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خوشه بندی فعالیت عضلات حمایت کننده لگنی در افراد با هایپرلوردوز کمری در فاز اتکای راه رفتن: رویکرد یادگیری ماشین

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چکیده

هدف: مقصود از مطالعه حاضر تعیین مؤثرترین فاکتور پیش‌بینی کننده هایپرلوردوز کمری از متغیرهای فعالیت عضلانی در فاز اتکای راه رفتن بود. بعلاوه، یافتن خوشه‌های همگن از افراد براساس فاکتور پیش‌بینی کننده مدنظر قرار گرفت.

روش شناسی: در این مطالعه فعالیت عضلات راست‌رانی، سرینی میانی و ارکتوراسپاین کمری در ۴۰ خانم مبتلا به هایپرلوردوز کمری حین راه رفتن ثبت شد. حداکثر فعالیت و هم‌انقباضی همه عضلات استخراج گردید. برای تعیین متغیرهای پیش‌بینی کننده هایپرلوردوز کمری، از شبکه عصبی پرسپترون چندلایه استفاده شد. سپس، خوشه‌بندی براساس مهم‌ترین فاکتور پیش‌بین با استفاده از خوشه بندی K-means برای یافتن خوشه‌های همگن از افراد مبتلا ب هایپرلوردوز کمری انجام گرفت. از آنووا یک سویه جهت یافتن خوشه‌های همگن استفاده شد.

نتایج: حداکثر فعالیت عضله راست‌رانی با دقت ٪۹۰,۹ به عنوان مهم‌ترین فاکتور پیش‌بین درنظر گرفته شد. همچنین آنووا یک سویه تفاوت معنادار بین سه خوشه همگن از افراد براساس حداکثر فعالیت عضله راست‌رانی را نشان داد($P \leq 0.05$).

نتیجه گیری: خوشه بندی ارائه شده در این مقاله می‌تواند برای توصیف الگوهای فعالیت عضلانی حین راه رفتن به‌کار رود؛ همچنین این نتایج می‌تواند برای غربالگری افراد مبتلا به هایپرلوردوز

کمری و تصمیم گیری بالینی مفید باشد. بعلاوه حداکثر فعالیت راست‌رانی به‌عنوان مهم‌ترین عامل مؤثر بر هایپرلوردوزکمری در این مقاله می‌تواند در زمینه توانبخشی و سلامت مورد توجه قرار گیرد.

واژه‌های کلیدی

راه رفتن، عضلات حمایت کننده لگنی، هایپرلوردوز کمری، یادگیری ماشین

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