Automatic diagnosis of lower back pain using gait patterns

Diagnóstico automático del dolor lumbar mediante patrones de marcha

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Pandey, CH.; Baghel. N.; Kishore-Dutta M.; Travieso, C. Automatic diagnosis of lower back pain using gait patterns. *Tecnología en Marcha*. Vol. 35, special issue. November, 2022. International Work Conference on Bioinspired Intelligence. Pág. 93-100.

https://doi.org/10.18845/tm.v35i8.6459

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Keywords
Gait Analysis; Back Pain; Support vector machine.

Abstract
Back pain is a common pain that mostly affects people of all ages and results in different types of disorders such as Obesity, Slipped disc, Scoliosis, and Osteoporosis, etc. The diagnosis of back pain disorder is difficult due to the extent affected by the disorder and exact biomechanical factors. This work presents a machine learning method to diagnose these disorders using the Gait monitoring system. It involves support vector machines that classify between lower back pain and normal, on the bases of 3 Gait patterns that are integrated pressure, the direction of progression, and CISP-ML. The proposed method uses 13 different features such as mean and standard deviation, etc. recorded from 62 subjects (30 normal and 32 with lower back pain). The features alone resulted in higher leave-one-out classification accuracy (LOOCV) 92%. The proposed method can be used for automatically diagnosing the lower back pain and its gait effects on the person. This model can be ported to small computing devices for self-diagnosis of lower back pain in a remote area.

Palabras clave
Análisis de la marcha; dolor de espalda; máquina de vectores de apoyo.

Resumen
El dolor de espalda es un dolor común que afecta principalmente a personas de todas las edades y da como resultado diferentes tipos de trastornos como obesidad, deslizamiento de disco, escoliosis y osteoporosis, etc. El diagnóstico del trastorno de dolor de espalda es difícil debido a la extensión del trastorno y factores biomecánicos exactos. Este trabajo presenta un método de aprendizaje automático para diagnosticar estos trastornos mediante el sistema de monitorización de la marcha. Se trata de máquinas de vectores de apoyo que clasifican entre lumbalgia y normal, sobre la base de 3 patrones de marcha que son la presión integrada, la dirección de progresión y CISP-ML. El método propuesto utiliza 13 características diferentes, como la desviación media y estándar, etc. registrado de 62 sujetos (30 normales y 32 con dolor lumbar). Las características por sí solas dieron como resultado una mayor precisión de clasificación de dejar uno fuera (LOOCV) del 92%. El método propuesto se puede utilizar para diagnosticar automáticamente el dolor lumbar y sus efectos sobre la marcha en la persona. Este modelo se puede transferir a pequeños dispositivos informáticos para el autodiagnóstico del dolor lumbar en un área remota.

Introduction
Back pain, commonly known as backache, is pain occurs mostly in the lower back section. The back has different parts that are classified into neck pain, also known as cervical, middle back pain also known as thoracic, lower back pain is also known as lumbar or coccydynia (tailbone or sacral pain) are part of the pain. [7, 9]. At the time of occurrence, Back pain may be chronic or acute, sub-acute, depending on the part. The pain may be of different types such as a dull ache piercing pain or shooting, or sometimes it gives a burning sensation. These types of pain can be analyzed with the help of gait data, with the help of gait analysis take at the events as one continuous gait motion [3]. After all, 15% of the average person's total weight was situated in the hip, thigh, lower leg, and foot comprise around. So, to understand how this weight is

transferred during walking is critical to preventing RSI and other injuries [7]. The study of Podiatric biomechanics uses the historic data of gait analysis. Musculoskeletal problems can occur with Gait abnormalities, such as back discomfort and changes in posture [3]. According to APA Frymoyer [9], Sportsperson and cross-country skiers are the Patients with moderate low-back pain has been more often pretentious when compared with the asymptomatic men with severe low back pain. Otherwise, there is no variability related to sports activity. The previous method use MRI, X-ray, and CT-Scan [10], which is costly and time taking process. The main object of this paper is to develop an easy and low-cost, lower back pain detection system using machine learning.

In this paper, we proposed an automatic diagnostic tool for a lower back pain using gait patterns based on the machine learning classifier. We have explored the features like a combination of integrated pressure, the centre of pressure, and the degree of a proposition for the lower back pain. We have also explored the statistical feature of these gait patterns to diagnose lower back pain using the SVM.

This paper is organized as follows. Section 2 describes the data uses and equipment details. Section 3 consists of a proposed methodology with data processing and feature extraction. In Section 4 described the experimental results and Section 5 describes the conclusion.

Dataset used

The Gait dataset is collected from Dr. Shakuntala Misra National Rehabilitation University, India, and was found 30-40% of people are infected with a different kind of back pain. The dataset is collected from The Proto Kinetics Zeno Walkway Gait Analysis System. Also, Proto Kinetics Movement Analysis Software is used that can effortlessly record and outputs temporal, spatial, and pressure measurements for various protocols. All data are stored in the form of an XML format that can be used to examine the gait of a subject.

The Gait monitor system contains a pressure sensing pad with dual control the sensor is embedded in a base layer, surrounded by a bevelled edge, the sensing pad connected with a system that analyses and record the sensor values and a camera set that is used to

Figure 1. A person of Age 42 diagnosed with back pain walking on the Gait monitor sensing pad and all required gait values are stored in the system with motion recording with the camera.

Table 1. Gait Dataset Explanation

Gait Values	Gender	Total subjects
Normal	Male –12, Female-18	30
Lower Back Pain	Male –16, Female-16	32
Total	Male-28, Female-34	62

The dataset was divided into two different categories, such as, 'Normal' and 'Lower Back pain'. The data consists of a total of 62 subjects (28 males and 34 females) where 30 subjects (12 Males and 18 Females) with Normal gait values and 32 subjects (16 Males and 16 females) suffering from back pain as shown in table 1.

Methodology

In this section, the proposed machine learning method for the identification of lower back pain using the gait pattern is described. It involves the processing of gait data of normal subjects and lowers back pain subject. To extract useful information from it for the training of a machine-learning algorithm to decide whether the gait data is lower back pain or not. It involves the steps of data processing, feature extraction, class labelling, etc., as discussed next.

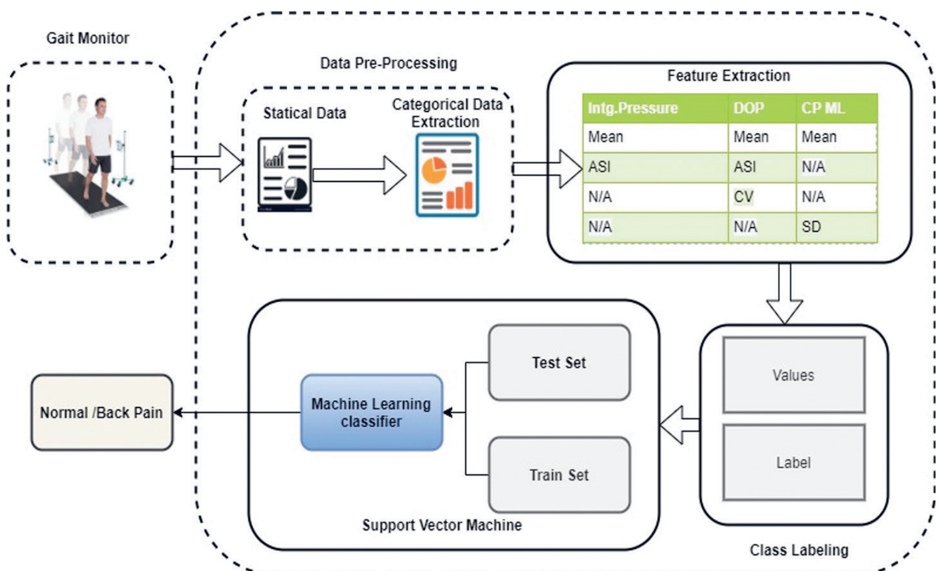

Figure 2. Flow diagram of a proposed algorithm.

Figure 2 gives the process flow obeyed in the proposed machine learning process for the diagnosis of lower back pain. Data generated from the gait monitor system is stoical data. It is preprocessed to extract categorical data from it, which discriminate values between lower back pain data and normal data. From the experimental study, three different gait patterns have been analyzed (i) the integrated pressure, (ii) the direction of progress, and (iii) the centre of propagation. Further, the statistical features of these categories have been used for training and testing of the proposed machine learning algorithm.

Feature extraction

The feature extraction is used to select the discriminate values that can be used to classify the normal gait data with lower back pain data. The proposed method has taken 3 gait patterns (Integrated pressure, the direction of progress, a centre of pressure) for the analysis. Integrated pressure (IP) measurement quantitatively characterizes the contact between the ground and foot. Clinical judgment of foot function mostly relies on the analysis of gait pressure and pressure-related framework under specific regions of the foot [12]. The shoulder joints, hip joints and the spine are known as "centre of mass" (COM). The median (in each coordinate) of these variables is considered the contemporaneous direction of progress (DOP) [13]. CISP-ML describes the shift of the Center of Pressure (CP) from the anterior-posterior axis of the Center of Origin Deviation is picked with a negative sign (–) if the positive (+) for an anterior shift and CISP-AP is shifted posteriorly. If it has deviated to the left a positive (+) value is applied and CISP-ML is shifted to the right it is picked with a negative sign (–) [14]. The statistical feature of these 3 gait patterns such as mean, left foot means, right foot means, accumulative swing index (ASI), coefficient of variation (CV), standard deviation (SD), SD left foot (SD LEFT), SD right foot (SD RIGHT), has been used for further analysis.

The proposed method has taken mean and variance from each sample data to determine the p values of the discriminant feature. The Extracted features of sample data and its corresponding p values are explained in table 2.

Table 2. Extracted features of sample data and its corresponding p-values.

S.no	Feature	Lower Back Pain Sample Value (Mean±Variance)	Normal Sample Value (Mean±Variance)	P values
1	IP Mean	179.4 ± 1822.1212	125.6086 ± 126.9452	2.33E-07
2	IP Mean(L)	178.9199 ± 1486.0614	165.8322 ± 1571.6691	0.04755059
3	IP Mean(R)	186.0457 ± 2443.3185	157.6840 ± 937.9480	0.001705977
4	IP ASI	-3.8332 ± 11.8333	4.5858 ± 6.61844	0.002133478
5	DoP Mean	-9.5851 ± 544.3209	-6.8516 ± 1980.9582	0.319169781
6	DoP Mean(L)	-28.8701 ± 505.89008	0.16193 ± 3667.4503	0.758613854
7	DoP Mean(R)	21.9554±1701.9548	-14.25426±1837.7280	0.571749924
8	Dop ASI	38.7139±3199.2950	-30.8834±9224.8274	0.939697302
9	Dop CV	-3796.234±278598765.71	15.7230±155342.5139	0.417152495
10	CPIML Mean	-2.1354±36.0454	-1.26973±5.02719	0.032416617
11	CPIML SD	-174.7287±201200.4723	845.0284±2693582.9156	0.15324072
12	CPIML SD(L)	-548.0343±2112559.7763	199.4138±633361.2656	0.353923927
13	CPIML SD(R)	-158.0511±99472.8081	-118.4832±510053.1774	0.789085173

In table 3 shows the features of the sample to find the most suitable features to implement. The mean and variance of these features are calculated for both normal and lower back pain suffering subjects. The P-values are calculated to check the prominent features using the probability of features.

Machine learning algorithm

A powerful supervised learning method is Support vector machine (SVM). Kernel function that is used in SVM plays an important for proper training of the SVM. There are various application in 1D signal [15,16]. In this work Linear Kernel is used for binary classification. The performance of classifiers is measured with different parameters like Sensitivity (Recall), Precision, Specificity, F1-Score, False Positive Rate, and Accuracy are used which are calculated as follows:

$$\text{Sensitivity(Recall)} = \text{TPTP+FN} \quad (1)$$

$$\text{Precision} = \text{TPTP+FP} \quad (2)$$

$$\text{F1 Score}=2^{*} \ \text{(Precision*Recall)/(Precision+Recall)} \quad (3)$$

$$\text{Accuracy}=\text{(TP+TN)/(TP+FP+TN+FN)} \quad (4)$$

Here true positive is denoted as TP, the total number of predicted values from a class A. True Negative is denoted by TN, which means the total number of predicted samples from class B. False Positive denoted by FP which means to express the total number class A gait values which are classified as class B. False-negative denoted by FN that means to defined the total number of class B Gait samples which are classified as class A.

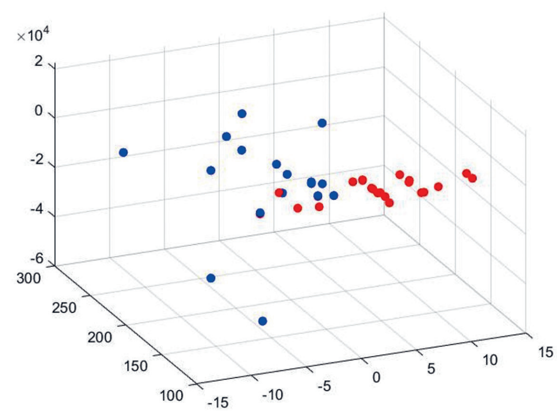

Figure 3. 3D Scatter plot of two Classes

Experimental Results

The proposed method used a Gait dataset with a total of 21 Statistical values for experimentation. It is classified into two different categories as healthy and lower back pain. The number of samples from healthy and lower back pain categories was 30 and 32, respectively. Due to a small dataset the "Leave-one-out-cross-validation (LOOCV)" has been used for cross-validation. The proposed method has been trained on SVM, knn, naïve Bais. The confusion matrix of these classifiers is shown in table 3.

Table 3. Testing set classification confusion matrix

		KNN classifier		Naïve bias classifier		SVM classifier	
True Label	Normal	32	0	26	6	30	2
	Lower Back Pain	30	0	2	28	3	27
		Normal	Lower Back Pain	Normal	Lower Back Pain	Normal	Lower Back Pain

Predicted values

In table 3 shows the confusion matrix of different classifiers (a) Knn classify 32 normal and 0 lower back pain, (b) naïve bais classify 26 normal and 28 lower back pain and (c) SVM classifies 30 normal and 27 lower back pain correctly. The performance of each classifier is compared with various parameters and it's described in table 4.

Table 4. Comparative performance of different classifier

Class	TP	FP	FN	TN	Precision	Recall	F1 score	Accuracy
Perfomance of KNN classifier								
Normal	32	0	30	0	0.00	0.00	0.00	
Lower Back Pain					0.52	1.00	0.68	0.52
Average					0.26	0.5	0.34	
Perfomance of Naïve bias classifier								
Normal	26	6	2	28	0.82	0.93	0.87	
Lower Back Pain					0.93	0.81	0.87	0.87
Average					0.875	0.87	0.87	
Perfomance of SVM clasiffier								
Normal	30	2	3	27	0.93	0.90	0.92	
Lower Back Pain					0.91	0.94	0.92	0.92
Average					0.92	0.92	0.92	

Table 5. Comparison of the proposed method against existing method

Reference	Methodology Used	Dataset	Accuracy
oameng Ung[7]	Structural MRI Data Detects Chronic Low Back Pain	MRI Dataset	76%
K Ritwik[8]	Analysis of lower back pain disorder using deep learning	LBP x-ray data	65%
Proposed Method	Special domain statistical and textural features classification using a Binary class support vector machine.	62 Gait Dataset	92%

The comparison of our proposed work with a similar kind of work is shown in table 4. The oameng [7] used an MRI dataset to detect Low Back Pain with 76% accuracy. K Ritwik [8] used X-ray to detect lower back pain using Deep learning.

Conclusions

A classification technique was used to recognize lower back pain with gait patterns. The overall test result indicated that the proposed method using the SVM classifier was able to effectively diagnose lower back pain conditions from a small contribution of 92% accuracy. This was encouraging for the future application of SVMs in gait diagnostics as well as in the assessment of treatment arbitration, especially in the lower back pain inhabitant. Future work may include multi-classification of various types of pain and the use of deep learning method to improve accuracy for the diagnosis of pain.

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