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Performance Analysis of Machine Learning Techniques with Dimension Reduction for Lower Back Pain Disorder

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ABSTRACT: Pain disorders such as lower back pain can occur to anyone at any age. Pain due to lower back injury is also common among people involved in heavy weight daily activities. It can be due to various reasons around different body parts which can include spinal cord, nerves in lower back region, core bones of the body structure or discs. Classification and categorization of persons with lower back pain is very important as effective treatment can be suggested for efficient cure. Many researchers had put in efforts and devoted significant time and resources for analyzing lower back problems but, it still remains an elementary medical issue among mass population. The main gap in research is the ability to identify the abnormal patients having lower back disorder using less number of features from the standard spine dataset. The major challenge in the study was to predict the category of the patients with minimum number of features having good prediction accuracy. This research work aims to determine the correlation between various features of primary data for lower back pain and performs classification using multiple machine learning algorithms (such as support vector machine, random forest, decision trees, and naive bayes) after removing most correlated feature. To achieve dimension reduction, principle component analysis and custom designed reduction technique was used. It categorizes patients having correct and incorrect backbone posture based on lower back data of 310 persons. Lower back pain spine dataset was taken from kaggle, and was used to carry predictive modeling. Such kind of study can be used for analysis of lower back for rehabilitation purpose.

Keywords: Classification, decision trees, k-nearest neighbor, lower back disorder, machine learning, navie bayes, random forest, support vector machine.

Abbreviations: POF, Plastic Optical Fiber; PCA, Principle Component Analysis; ML, Machine Learning; DR, Dimension Reduction; PC, Principle Components; LDA, Linear Discriminant Analysis; KDA, Kernel Discriminant Analysis; SVM, Support Vector Machine; RF, Random Forest; DT, Decision Trees, NB, Naive Bayes; KNN, K-Neaest Neighbour.

I. INTRODUCTION

Nowadays due to busy and sedentary lifestyle, lower back pain disorders are very common amongst majority of the population. Due to presence of such disorders, performance of our daily activities is affected significantly which further reduces the effectiveness of the person. Ignorance of such cases may lead to severe problems in later stages, hence it is important to find and mitigate the basic causes. The issue with such disorders is that in some cases the cause can be very specific and in some, may not be precisely known. Oliverio *et al.,* (2017) mentioned that pelvic region pain issues are very common in developed countries where many people lead a sedentary life style [1]. According to the author a majority of lower back pain related issues arises for the first time in early twenties. The probability of recurrence in later years of one's life is high and can convert to severe chronic disorders in absence of proper treatment and medical supervision. Some of the reasons for lower back pain occurrence as discussed by Gaonkar *et al.*, (2017) includes irritation or suppression in large nerve roots present in lower back region, strain in small nerves connected to the lower back, strain in large muscles in spine, and damaged bones or ligaments, to identify a few [2]. Taghvaei *et al.,* (2017) discussed an important lower back issue which deals with difficulty in movement by elderly persons to perform daily activities. This could happen due to lack of muscular strength, musculo-skeletal injuries, and lower back pain [3]. Du *et al.*, (2018) stated in their research work that medicines or surgeries are required for persons with acute lower back pain in order to improve the health condition [4]. In order to avoid use of such medication or undergo surgeries it is necessary to analyze data of the lower back collected from the patients and opt for corrective measures before it converts to severe back pain. Another important finding, mentioned by Nassar *et al.*, [5] is that there is strong influence of depression on pain severity and amount of disability among persons having chronic lower back pain.

Under normal condition, a healthy inter-vertebral disc is present between adjacent vertebrae in the vertebral column. Due to its presence, the human spine does not feel sudden shocks as it acts like a shock absorber for the entire spine. Under many conditions it may degenerate which causes trouble with some of the structures in the vertebral column and can cause severe pain. This is considered as one of the reasons of having pain in areas of the body which are linked to the spine. Such situations can also give rise to problems of back muscle spasms causing severe pain in upper, middle or lower back. Being a common pain related issue in a majority of population its symptoms and pain severity may vary greatly. This is probably due to the different routes of degeneration of the inter-vertebral dics as schematically shown in Fig. 1.

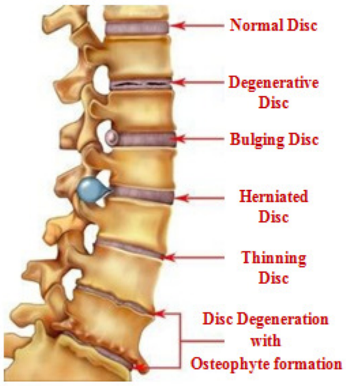

Fig. 1. Different types of disc problems [6].

Brief description of different types of inter-vertebral disc degenerations between adjacent vertebrae in the vertebral column of the human spine are given below, in support of Fig. 1.

– Normal Disc: The proper disc structure which helps in absorbing shocks between adjacent vertebrae in the vertebral column.

– De-generative Disc: The effectiveness of the disc as a shock absorbers is reduced, either due to thinning or erosion of the disc, resulting in occurrence of pain in surrounding areas.

– Bulging Disc: There is an increase in the space between adjacent vertebrae due to an increase in volume which results in continuous pain in the surrounding areas of the affected region.

– Herniated Disc: A portion of the disc pushes through the crack in the annulus. Also referred to as a slipped disc or ruptured disc, it leads to irritation in any nearby nerve, which further results in pain.

– Thinning Disc: Loss of water in the body causes the discs to thin, resulting in a reduction of the distance between adjacent vertebrae.

– Disc Degeneration with Osteophyte Formation: Osteophytes formation occurs in case of degenerative disc disease, osteoarthritis, spinal stenosis, etc. The normal bone growth tends to get influenced by swollen or damaged tissues. Hence, osteophyte formation develops with formation of new bone cells and get deposited in the unwanted region.

Hence it is very important that the different parameters related to lower back pain be measured and studied to understand the correlation between the different attributes. Some of the important features which can be analyzed using machine learning techniques for lower back pain disorders are direct tilt, pelvic radius, degree spondylolisthesis, cervical tilt, sacral slope, pelvic slope, scoliosis slope, pelvic incidence, sacrum angle, lumbar lordosis angle, pelvic tilt, and thoracic slope.

With the different advances in electronics technology, in recent years, various different types of sensors have been used to analyze body movements and perform data acquisition using different sensors. Data using such efforts have been further used to perform classification of patients having lower back problems. Urukalo *et al.,* (2018) had designed a wearable system to find and analyze problems related to lower back pain and some musculo-skeletal disorders [7]. Molnar *et al.,* (2018) used multi dimensional (6D) Inertial Measurement Units (IMUs) to capture lower back data while performing body movements [8]. Xu *et al.,* (2018) proposed an algorithm which did not use any ground reference for angle calculation and instead used the angle formed between two IMU sensors modules [9]. Chutatape *et al.,* (2017) had implemented a system using one smart phone and measured joint angles at hip location which led to inappropriate body postures and could result in dislocation of joint [10]. Kam *et al.,* (2017) had designed a sensor using on POF (i.e. plastic optical fiber). An Intensity Interrogation Technique (I^2) was used to analyze bending of back bone curvature in sagittal plane [11]. Dobrea *et al.,* (2018) implemented a wearable warning system which identified an improper sitting posture. The above was performed by the concept of multiple triggering zones and finding system presence in those zones [12].

However, development of hardware as mentioned above was an important factor to identify lower back pain, data processing and classification of patients is also important. Sandag *et al.,* (2018) presented machine learning algorithm for selected subjects with pain in lower back region and used K-Nearest Neighbor (KNN) classifier on non real time data [13]. The authors had observed that Degree Spondylolisthesis parameter had the highest significance in having effect on lower back pain conditions. Jenkins *et al.,* (2002) had presented a technique which could classify patients with pain in lower back region into two categories viz. chiropractic or pathological [14]. Darasi *et al.,* (2013) identified disc diseases such as de-generative disc using a fuzzy technique [15]. The procedure consists of a chaining approach both in forward and backward direction in its inference engine. Sullivan (2005) performed identification and categorization of patients having lower back pain by using the mechanism of maladaptive movement [16].

The main drawback of the literature review was that the classification of patients based on minimum number of spino-pelvic parameters with high classification accuracy was not done. In this article we compare the different types of classification algorithms operated on lower back spine data. Dimension reduction techniques such as Principal Component Analysis (PCA) were also used. Multiple special cases were also implemented for dimension reduction to analyze the classification accuracy on the basis of removal of most correlated features. The main advantage of the proposed research work is the ability to classify patients with abnormal back posture even if all spino-pelvic parameters are not available.

II. MATHEMATIACL PRINCIPLE

Several of the most relevant and prominent machine learning algorithms have been used in this article to convey their effectiveness for the given dataset. A schematic flowchart of the steps involved are shown and explained in Fig. 2.

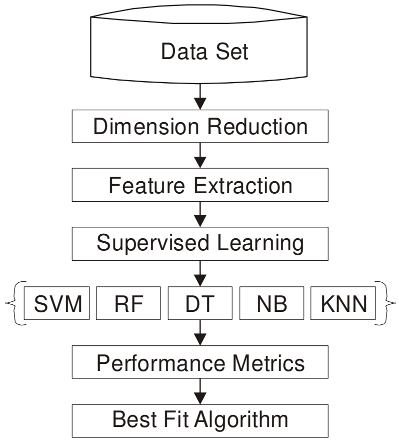

Fig. 2. Flow diagram of the complete system.

Different Machine Learning (ML) techniques can be implemented on the spine data set by using original features or after performing Dimension Reduction (DR). DR is often used, especially in the development of machine learning algorithms, to reduce the number of attributes as well as the computational requirements. Further, it also allows in the development of optimized hardware that can perform the same task, with reduced hardware. DR can be implemented using various techniques viz. Linear Discriminant Analysis (LDA), Principle Component Analysis (PCA), and Kernel Discriminant Analysis (KDA). Due to the reduction in dimensions, there is also a chance for information loss. However, this can be overcome by an appropriate supervised ML, but is always an issue for unsupervised techniques. Another important step which was used in implementation of Machine Learning algorithms was pre-processing of data before dimensionality reduction. After completion of the pre-processing task and deduction in number of features, feature extraction was performed to extracts features form the dataset. The data was used to perform supervised learning using different techniques using Support Vector Machine (SVM), Random Forest (RF), Decision Trees (DT), Naive Bayes (NB), and K-Nearest Neighbor (KNN). To implement the above mentioned classification algorithms dataset was segregated into 2 sets viz. TR_{set} i.e. training set used to train the classification algorithm and TE_{set} i.e. testing set used to predict the output class from the trained classification algorithms. In the present research work various classifiers were used to perform classification of patients having lower back pain disorders. A comparison of performance metrics of different classifiers were carried out to find the best suited classifier for the given case. Shabrina *et al.,* (2018) used visual analogue scales and pain questionnaire methods to analyze lower back pain due to prolonged standing on inclined surface [17]. Some of the important features which can be analyzed using machine learning techniques for lower back pain disorders are direct tilt, pelvic radius, degree spondylolisthesis, cervical tilt, sacral slope, pelvic slope, scoliosis slope, pelvic incidence, sacrum angle, lumbar lordosis angle, pelvic tilt, and thoracic slope. Hence to further this avenue of research, the present article highlights the relevance of the most important feature used to implement classification using different algorithms.

PCA is an important DR technique which is based on conversion of original features into principle components. It is implemented on multi dimensional data for reducing the dimension and obtaining principle components. It is a technique which converts features of any dataset into a set of features which were not correlated to each other (also known as PC or Principle Components). The total number of obtained PCs was less than the number of original features in the spine dataset. In this research work total principal components were restricted to two (i.e. PC_1 and PC_2). PC_1 had the highest variance, which would make it orthogonal to PC_2 which also had the highest variance under the constraint of orthogonal components. These two principal components were uncorrelated orthogonal samples.

Mathematically, the conversion in PCA was explained as a model having a set vectors with p dimensions with weights $w_1, w_2, \ldots w_p$, such as given in Eqn. 1,

$$w_{(k)} = (w_1, \ldots w_p)_k \tag{1}$$

This will change all row vector $x_1, x_2, \ldots x_m$ of set X to a new vector having all principal components as given in Eqn. 2,

$$t_{(i)} = (t_1, \ldots t_m)_i \tag{2}$$

The mapping of all row vectors into vectors having principal components were performed using Eqn. 3, where; range of i and k were defined as, i = 1, ..., n and k = 1, ..., m.

$$t_{k_{(i)}} = x_i . w_k \tag{3}$$

The above mapping as defined in Eqn. 3 was performed in a manner that all variables in set t throughout spine dataset, successively take maximum variance which is possible from x. In this mapping all weighted vectors w, were restricted as a single unit vector. The authors have carried PCA on 12 dimensional vectors which converged into individual weighted vectors. Loading the first vector w_1 has to satisfy Eqn. 4,

$$w_1 = argmax_{||w||=1}\{\textstyle\sum_{i=1}(t_1)^2_{(i)}\} = argmax_{||w||=1}\{\textstyle\sum_{i=1}(x_i . w)^2\} \tag{4}$$

Since w_1 was defined as a unit vector, so it also satisfies condition mentioned in Eqn. 5,

$$w_1 = argmax\left\{\frac{w^T X^T X_w}{w^T w}\right\} \tag{5}$$

Finally, the reduction in dimension is achieved by performing the conversion, T= XW from p-dimensional set of original features to a transformed set of p-dimension uncorrelated features for the spine dataset. Now, truncation of features was performed by keeping only the first L principal components (as PC_1, PC_2, ..., PC_L), which were obtained with the help of first L weighted vectors as shown in Eqn. 6,

$$T_L = XW_L \tag{6}$$

Implementation of PCA as a DR technique eliminates the outliner completely and hence the modified data with reduced dimension is used for analysis.

III. SOFTWARE ANALYSIS

After getting principal components having minimal covariance between various features, multiple machine learning algorithms are implemented on the dataset. Referring to Fig. 2, multiple classification algorithms were used under supervised learning. In this the entire spine dataset was divided in TR_{set} (i.e. training set) and TS_{set} (i.e. testing set). The training set consists to the sample which was used to train the classifier and the testing set consists of the samples which were need to be tested by the trained classifiers. In this learning environment, each sample consists of input features and an output target class. The best solution will allow the classifiers to have 100% classification accuracy which correctly predicts the target class for any new test input data. But in case of data related to lower back pain disorder, it was difficult to achieve high accuracy values very close to 100% as the patient condition vary in a diversified manner from person to person. Eighty five percent of the patients with lower back disorders having no symptoms at all leads to a classification [16]. Supervised learning techniques are divided into two parts: Base Level techniques and Ensemble learning techniques [18]. Base Level classification algorithms are the traditional classification algorithms such as Naive Bayes, Support Vector Machine, etc. Ensemble classification algorithms are the techniques which combine multiple learning techniques and come up with a single predictive algorithm in order to improve prediction accuracy.

K-Nearest Neighbor classifier (KNN) was one of the classifier which was used in this research work. It is known as a nonparametric algorithm which does not require any parameter for classification. It has input samples and output class where the input comprises of 'K' nearest samples from the training set. When KNN used for classification, it predicts the target class for any new test sample from the testing set. An object of the testing input was categorized based on maximum votes from its neighbors, and this same object was assigned to one of the target class having highest occurrence among its 'K' nearest neighbors. The K-Nearest Neighbor classifier, assigns the weight value of 1/k to the 'K' nearest neighbors and weight value 0 is assigned to all the remaining neighbors.

Present research work also used Support Vector Machine (SVM) technique to perform categorization of the persons having back pain disorder issues. SVM classifier was implemented as it used structural risk minimization as compared to empirical risk minimization. Misclassification error in case of SVM could be reduced by using empirical risk with the samples from the training dataset. On the other hand, probability of wrongly categorizing a new sample data from testing set could be reduced by using structural risk.

Random Forests (RF) is a type of ensemble learning technique which was also implemented in this research work to classify lower back pain patients. It works on the principle of creating a multilevel Decision Tree while training was performed for the classifier. It predicts the target class which was calculated as the mode of all target class values for the individual decision trees.

Another classifier i.e. Naive Bayes is a probabilistic classifier, which is having Bayes' theorem as the working principle behind it. It assumes a strong independence between different features of the spine dataset that means that the features were not related to each other. It was selected as it was one of the simplest Bayesian network model. An important aspect of this algorithm was that it was highly scalable which requires a number of parameters having linear nature for number of features in a particular learning problem.

The data which was used for this research work was taken from an online data repository; Kaggle. In similar manner the classification algorithms were implemented by Lydia *et al.*, (2019) for analyzing the performance of classification algorithms on disease datasets [19]. The dataset used in this article was the spine dataset which comprises of 310 samples for lower back pain and 12 numeric predictors and single target class attribute with binary values as normal and abnormal. The spine data provides hidden information for identification of a person, which helps to find whether the person comes under abnormal category or normal category. Table 1 shows summary of the spine dataset used for this research work mentioning names of all used features.

Table 1: Summary of Dataset.

Number of Records	310
Number of Attributes	12
Type of Classification	Binary
Number Classifiers	5
Data Type of Features	Numeric
Data Type of Target Class	Text

Table 2 shows important description of 12 numeric features of spine dataset. It was seen that the standard deviation in case of degree-spondylolisthesis was 37.5 which is maximum among all features and in case of pelvic-slope was 0.29 which was minimum among all features. Standard deviation and variance of attributes plays an important role in case of dimension reduction in any dataset. Due various dimension reduction techniques such as PCA, LDA, and KDA on the dataset, the computation time required for any classification algorithm also reduces and execution becomes fast as compared to classification results achieved using all original features.

Table 2: Feature description of spine dataset.

Feature Name	Mean	Std.	Min.	Max.
pelvic-incidence	60.5	17.2	26.1	130
pelvic-tilt	17.5	9.99	-6.55	49.4
lumbar-lordosis-angle	51.9	18.5	14	126
sacral-slope	43	13.4	13.4	121
pelvic-radius	118	13.3	70.1	163
Degree-spondylolisthesis	26.3	37.5	-11.1	419
pelvic-slope	0.47	0.29	0	1
Direct-tilt	21.3	8.63	7.03	36.7
thoracic-slope	13.1	3.39	7.04	19.3
cervical-tilt	11.9	2.89	7.03	16.8
sacrum-angle	-14.1	12.2	-35.3	6.97
scoliosis-slope	25.6	10.4	7.01	44.3

IV. RESULTS AND DISCUSSIONS

The classification was performed on spine dataset using multiple classifiers viz. Naive Bayes, Support Vector Machine, Decision Trees, K-Nearest Neighbor, and Random Forest. Table 3 shows the performance metrics of all classifiers which was used to perform classification on the spine dataset using original features and finally used for prediction of any new test data. The prediction was binary in nature and was done using two prediction target classes (i.e. Abnormal- mapped as numeric '0', and Normal- mapped as numeric '1'). The classifiers are denoted by 'Clf' in Table 3 and details of other abbreviation for performance metrics are given as 'Acc': Accuracy; 'F1': F1 Score; 'Sen': Sensitivity; 'Spec': Specificity; 'Pre': Precision; 'Time': Computation Time in seconds.

Table 3: Performance of various classifiers.

Clf	Acc	F1	Sen.	Spec	Pre	Time
NB	76.69	0.70	0.84	0.72	0.59	0.002
SVM	87.37	0.81	0.87	0.87	0.76	0.005
DT	82.52	0.70	0.63	0.91	0.77	0.003
KNN	81.04	0.72	0.78	0.82	0.67	0.070
RF	73.78	0.59	0.60	0.80	0.58	0.078

Table 4 shows confusion matrix of Naive Bayes classifier after performing classification on the spine dataset with original features. In this, AB_{Act} and N_{Act} were the actual class values for the Abnormal and Normal target class denoted by '0'and '1' respectively. Whereas, AB_{Pre} and N_{Pre} were the predicted class values for the Abnormal and Normal target class denoted by '0' and '1' respectively. The accuracy was calculated as 76.69% with 0.70 as F1 Score. It also had the least computation time of 0.002 seconds only.

Table 4: Confusion matrix of NB classifier.

	$AB_{Pre}(0)$	$N_{Pre}(1)$
$AB_{Act}(0)$	51	19
$N_{Act}(1)$	5	28

Table 5 shows confusion matrix of Support Vector Machine classifier after performing classification on the spine dataset with original features. The accuracy was calculated as 87.37% with 0.81 as F1 Score. Among all classifiers which were used, SVM had the highest accuracy and small computation time of 0.005 seconds.

Table 5: Confusion matrix of SVM classifier.

	$AB_{Pre}(0)$	$N_{Pre}(1)$
$AB_{Act}(0)$	61	9
$N_{Act}(1)$	4	29

Table 6 shows confusion matrix of Decision Tree classifier after performing classification on the spine dataset with original features. The accuracy was calculated as 82.52% with 0.70 as F1 Score. It was having second best accuracy after SVM classifier and second best computation time of 0.003 seconds. It also had highest 'Specificity' of 0.91 among all 5 classifiers which was used in this research work.

Table 6: Confusion matrix of DT classifier.

	$AB_{Pre}(0)$	$N_{Pre}(1)$
$AB_{Act}(0)$	64	6
$N_{Act}(1)$	12	21

Table 7 shows confusion matrix of K-Nearest Neighbor classifier after performing classification on the spine dataset with original features. The accuracy was calculated as 81.04% with 0.72 as F1 Score. It was having high computation time of 0.07 seconds as compared to NB, SVM, and DT classifiers.

Table 7: Confusion matrix KNN classifier.

	$AB_{Pre}(0)$	$N_{Pre}(1)$
$AB_{Act}(0)$	138	30
$N_{Act}(1)$	17	63

Table 8 shows confusion matrix of Random Forest classifier after performing classification on the spine dataset with original features. The accuracy was calculated as 73.78% with 0.59 as F1 Score. It was having least F1 Score among all implemented classifiers and was having maximum computation time of 0.078 seconds.

Table 8: Confusion matrix of RF classifier.

	$AB_{Pre}(0)$	$N_{Pre}(1)$
$AB_{Act}(0)$	56	14
$N_{Act}(1)$	13	20

As discussed earlier, that various dimension reduction techniques such as PCA, LDA and KDA could be used to reduce total number of features required to perform classification on spine dataset, Fig. 3 shows plotting of two principal components viz. PC1 and PC2 after performing PCA on the spine dataset.

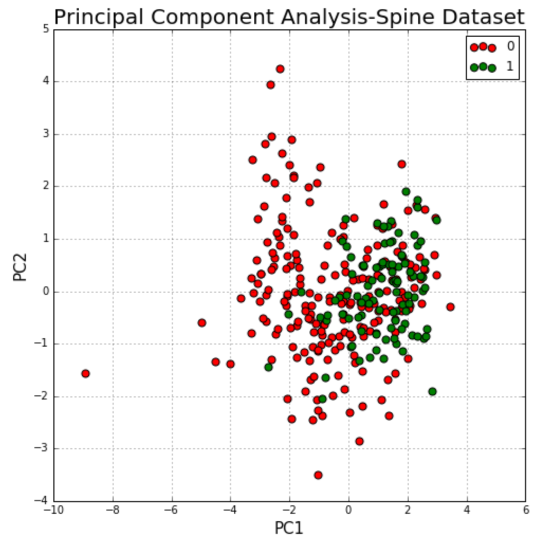

Fig. 3. PCA on spine dataset.

Different classifiers viz. NB, SVM, DT, and RF which were also used with original features in this research work were then implemented to perform classification after performing PCA on spine dataset. It was observed with these classifiers that after performing Principal Component Analysis of the spine dataset performance metrics such as accuracy and F1 Score reduces. The reduction in accuracy shows that PCA leading to two principal components was not recommended for dimension reduction on spine related data and lower back pain analysis as classification becomes less accurate after performing PCA.

Table 9 shows the accuracy achieved by different classifiers after performing PCA on the original features of spine dataset. It was found that there was a decrease in accuracy for all classifiers. This decrease was calculated as 11.65 for Naïve Bayes, 19.41 for Support Vector Machine, 21.36 for Decision Trees, and 10.68 for Random Forest classifier. Hence it was found that PCA leading to two principal components was not suitable for dimension reduction in case of data related to lower back analysis such as spine dataset which was used in this research work.

Table 9: Classification accuracy PCA.

Classifiers	NB	SVM	DT	RF
Accuracy	65.04	67.96	61.16	63.10

To figure out other alternatives for dimension reduction, correlation between various features of spine dataset was calculated. The correlation matrix for the used dataset is shown in Table 10. The correlation coefficients in the correlation matrix will always be between 0 (min) and 1 (max). Maximum value of 1 for the correlation coefficient, means 100% similarity between corresponding features. On the other hand if the minimum value of 0 is obtained for the correlation coefficient, it shows that corresponding features are independent of each other and were having 100% distinct values with zero relation with each other. From the calculated correlation coefficients it was observed that there was high correlation between Col1-Col2, Col1-Col3, Col1-Col4, Col1-Col6, Col3-Col4, Col3-Col6, and Col4-Col6; where Col1 to Col12 are the labels assigned to spino-pelvic parameters.

The mapping between labels and actual parameters is given below:

– Col1 is mapped to degree spondylolisthesis
– Col2 is mapped to pelvic incidence
– Col3 is mapped to pelvic tilt
– Col4 is mapped to lumbar lordosis angle
– Col5 is mapped to sacral slope
– Col6 is mapped to pelvic radius
– Col7 is mapped to pelvic slope
– Col8 is mapped to direct tilt
– Col9 is mapped to thoracic slope
– Col10 is mapped to cervical tilt
– Col11 is mapped to sacrum angle
– Col12 is mapped to scoliosis slop.

Table 10: Correlation coefficients of all spino-pelvic parameters used.

	Col1	Col2	Col3	Col4	Col5	Col6	Col7	Col8	Col9	Col10	Col11	Col12
Col1	1	0.629	0.717	0.814	-0.247	0.638	0.043	-0.078	-0.089	0.016	0.019	-0.007
Col2	0.629	1	0.432	0.062	0.032	0.397	0.008	-0.072	-0.063	0.028	0.032	-0.056
Col3	0.717	0.432	1	0.598	-0.080	0.533	0.029	-0.112	-0.063	0.063	0.057	-0.049
Col4	0.814	0.062	0.598	1	-0.342	0.523	0.048	-0.046	-0.067	0	0	0.032
Col5	-0.247	0.032	-0.080	-0.342	1	-0.026	0.015	0.063	0.060	-0.039	0.029	-0.030
Col6	0.638	0.397	0.533	0.523	-0.026	1	0.085	-0.063	-0.057	0.056	0.023	-0.041
Col7	0.043	0.008	0.029	0.048	0.015	0.085	1	0.012	-0.011	0.088	0.060	-0.073
Col8	-0.078	-0.072	-0.112	-0.046	0.063	-0.063	0.012	1	0.009	0.072	-0.037	-0.024
Col9	-0.089	-0.063	-0.063	-0.067	0.060	-0.057	-0.011	0.009	1	0.052	0.011	0.009
Col10	0.016	0.028	0.063	0	-0.039	0.056	0.088	0.072	0.052	1	0.057	0.021
Col11	0.019	0.032	0.057	0	0.029	0.023	0.060	-0.037	0.011	0.057	1	0.015
Col12	-0.007	-0.056	-0.049	0.032	-0.030	-0.041	-0.073	-0.024	0.009	0.021	0.015	1

To achieve dimension reduction of spine dataset which would off load the computation process at the time of classification, correlated features were identified using correlation matrix. From the correlation matrix it was observed that degree spondylolisthesis was the most significant and most correlated feature when analyzing lower back pain disorder. It is defined as the forward displacement of one vertebra over another. It generally happens between the 5^{th} and 6^{th} lumbar vertebra. It was also observed that lower back pain disorder could be classified as normal or abnormal without using most significant feature with only minor reduction in classification accuracy in case of NB and DT classifiers as shown in Table 11.

Table 11: Classification accuracy after removing most correlated feature from the spine dataset.

	NB	SVM	DT	RF
Accuracy	73.78	72.81	79.61	68.93
Computation Time	0.002	0.006	0.003	0.044

Further, the performance of all four classifiers were measured in special five cases denoted by case 1, 2, 3, 4 and 5; where case 1 represent dataset after removal of Col6 feature, case 2 represent dataset after removal of Col6 and Col1 features, case 3 represent dataset after removal of Col6, Col1, and Col3 features, case 4 represent dataset after removal of Col6, Col1, Col3, and Col4 features, and finally case 5 represent dataset after removal of Col6, Col1, Col3, Col4, Col5, Col7 and Col9 features. It was shown in Table 12 that performance in terms of accuracy of all four classifiers, in all five cases was less than the classification accuracy when original features were used as it was given in Table 12.

Table 12: Classification accuracy with special dimension reduction cases from the spine dataset.

Clf	Case 1	Case 2	Case 3	Case 4	Case 5
NB	73.78	74.75	76.69	73.78	64.07
SVM	72.81	72.81	72.81	70.87	62.13
DT	79.61	77.66	77.66	77.66	61.16
RN	68.93	69.90	70.87	67.96	66.99

Fig. 4 shows line plots for performance measure i.e. accuracy for all four classifiers. It was seen that there was a sudden drop in classification accuracy from case 4 to 5 for Naive Bayes, Support Vector Machine, and Decision Tree classifiers. The case 5 accuracy was also less than the accuracy achieved after implementation of PCA with two principal components for naive Bayes, Support Vector Machine, and Decision Tree classifiers.

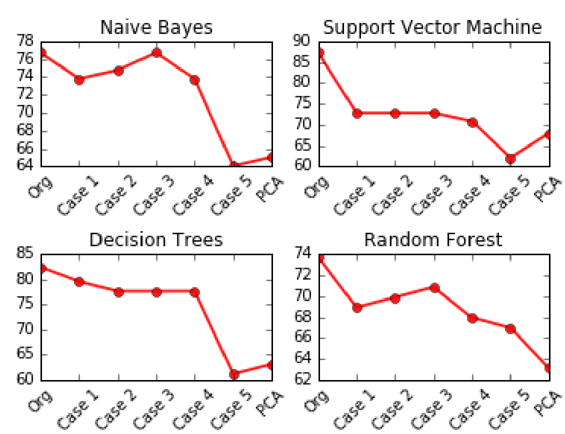

Fig. 4. Classification accuracy plots original features, special cases, and PCA analysis.

It was also seen that accuracy almost remained fixed for Support Vector Machine classifier for case 1, 2 and 3. This behavior was also seen with Decision Tree Classifier for case 2, 3 and 4.

V. CONCLUSION

Lower back pain is not a disease but can be summarized as collection of symptoms in body postures and daily activities. Low back pain can also cause disability which can result in heavy socioeconomic burden on developed and developing countries. This research work resulted in analysis and classification of lower back pain disorder patients into two categories viz. normal and abnormal. The classification was performed using five classifiers namely, Naive Bayes, Support Vector Machine, Decision Trees, K-Nearest Neighbor, and Random Forest. It was also found that SVM was having the highest classification accuracy of 87.37% among all used classifiers when classification was performed using original features. It was also observed that accuracy of classification substantially reduces when it was performed when PCA was implemented for dimension reduction with converted dataset having two principal components. Hence, correlation was found between features and classification was performed after removal of highly correlated feature by creating different cases where different set of features were removed. It showed small variation in classification accuracy in case of Naive Bayes, Support Vector Machine, and Decision Tree. It was seen that classification accuracy almost remained constant for three cases for Support Vector Machine and it showed same behavior for another set three cases for Decision Tree classifier. It was also observed that after removal of seven features from the original spine dataset, the classification accuracy drops down below the classification accuracy achieved in case of PCA implementation.

In present research work, it was found that to perform classification with dimension reduction, for lower back pain disorder patients, maximum of four most correlated features could be removed to achieve high accuracy. The accuracy achieved with dimension reduction was close to the calculated accuracy of classifiers implemented on a set of original features.

VI. FUTURE SCOPE

In future, this research work could be carried further to find an alternative way of dimension reduction, which can achieve reasonably high classification accuracy close to the one achieved with original features even after removing more features from the spine dataset. The classifiers could also be implemented to have multiple target classes where the target class could have more than two categories.

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Conflict of Interest. The authors declare that they have no conflict of interest.

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