A Machine Learning Approach for the Classification of Lower Back Pain in the Human Body

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***Abstract*—The 21*st* century has been witnessing a high growth in technology in every field including the medical sector. Dynamic systems have been designed and implied for better and accurate diagnosis of a large variety of ailments; but, the growing number of patients makes it difficult to provide proper medical attention in time. To overcome this difficulty, Intelligent Systems techniques can be employed in the medical sector and help us overcome the huge difference in the ratio of doctors versus patients; along with reducing the examination and waiting time for the patients. Among all the variety of ailments prevailing in today's world, "Lower Back Pain" has emerged as one of the most prevailing ailments which includes around 80% of the total population once in lifetime, making it to one of the prior concerns of medical sector. To act effectively onto it, many conventional methods have been used to diagnose lower back pain. This study aims to design a non-Conventional technique to classify Lower back pain either Normal or Abnormal using Machine Learning techniques such as Naïve Bayes, Support Vector Machines, Decision Trees, Gradient Boosted Trees, Fast Large Margin, K Nearest Neighbor, Multilayer Perceptron, Random Forest, and Artificial Neural Networks. This research focuses upon the implementation of the above-mentioned techniques for the proper classification of Spine Dataset and for determining the best technique in terms of Accuracy, Precision, Sensitivity, Specificity, F-measure and Area under Curve.**

***Index Terms*—Machine learning, lower back pain, automatic feature engineering technique. performance evaluation.**

I. INTRODUCTION

The hustle in today's life brings a lot of unwanted and chronic ailments with it. Physical and Mental stress affects the body in many undesirable ways and brings many ailments to it. Lower Back Pain is one such disorder which has affected near about half the population on this planet including all age groups [1]. Its proper and timely treatment is a must, as ignorance may lead to its conversion to a chronic disorder. Therefore, its proper diagnosis by chiropractors is necessary. But the vast gap in the ratio of the number of chiropractors to the number of patients increases the demand of urgent attention to the cases of lower back pain in order to get rid of it. Majorly back pain is mechanical in nature with some of its causes mentioned as Sprains and strains, Intervertebral disc generations, Ruptured disc, Spondylosis, Injury, Infection, Tumor, Skeletal irregularities, Spinal stenosis, Sciatica, Radiculopathy, Abdominal aortic aneurysms [2]. For proper diagnosis doctors have to go through the results of certain tests which includes physical examination, analyzing X-ray results, CT scans, Scan bones, Ultrasound Imaging and other necessary reports. This takes a lot of time which in turn extends the waiting time for rest of patients. Also, many times it happens that the doctors find it quite difficult in determining the type of pain whether normal or abnormal which further delays the treatment for other patients. Usually Normal or Acute Back Pain gets vanished in 4-12 weeks but if the pain is sustaining even after 12 weeks, then the Lower Back Pain is Abnormal Lower Back Pain. Chronic back pain or commonly termed as Abnormal back pain is generally caused due to some disease [3]. Treatment of lower back pain depends upon whether it is acute or chronic, which can be determined only after proper diagnosis. For complete diagnosis, the doctors have to undergo the results of certain imaging scans and tests conducted. To overcome this, certain non-conventional techniques are studied and implemented in this research to diagnose LBP. Here, an on-line publicly available dataset is used to develop computational fast models that give a reliable decision. For this study, 11 Machine Learning based classification models have been considered and whose names are shown in the table I below. Performance evaluation of these models are done and a "best" model is selected for each performance parameter.

TABLE I: MACHINE LEARNING CLASSIFIERS USED IN THIS RESEARCH

Sr. No.	Machine Learning Classifiers
1	Naïve Bayes Classifier
2	Logistic Regression Classifier
3	Deep Learning Classifier
4	Random Forest Classifier
5	Support Vector Machines Classifier
6	Decision Trees Classifier
7	Gradient Boosted Trees Classifier
8	Multilayer Perceptron Classifier
9	Artificial Neural Network Classifier
10	K-nearest Neighbor Classifier
11	Fast Large Margin Classifier

The Dataset is retrieved from a website named Kaggle [4]. The Dataset consists of 13 columns out of which first 12 columns are called Pelvic Parameters, or Range of Motion Attributes, and the 13th column decides whether type of Lower Back Pain is Normal or Abnormal for that particular data. Change in the values of Pelvic Parameters cause Lower Back Pain. The values of these parameters are normally measured by Radiographs, X-rays, Inclinometers and Goniometers. A very brief description of each pelvic parameter considered in this study is provided in Table II.

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TABLE II: BRIEF INTRODUCTION OF PELVIC PARAMETERS [5]

Sr. No.	Parameter	Definition/ Feature
1	Pelvic Incidence	Angle between the perpendicular to the sacral plate at its midpoint and the line connecting this point to the femoral heads. Normal Value is 50 º
2	Pelvic Tilt	Orientation of the pelvis in respect to the thigh bones and the rest of the human body.
3	Sacral inclination	The angle between the vertical plane and the tangential line to the sacral vertebrae.
4	Lumbar Lordosis	Normal inward curvature of the lumbar (lower) and cervical regions of the human spinal cord. Ranges from 39 º-53 º
5	Pelvic Radius	Distance between PR lines to the horizontal.
6	Degree Spondylolisthesis	Evaluated by its degree of spinal slip or spinal deformity.
7	Pelvic Slope	Angle between the horizontal plane and the plane of pelvic– inlet.
8	Direct Tilt	Angle made by a line running from the sacral end plate midpoint to the center of the bi-femoral heads.
9	Thoracic Slope	Angle between a plumb line of cord and a straight line from the first thoracic vertebra (T1) to the first sacral vertebra (S1).
10	Cervical Tilt	Parameter in neck region of the spinal column is known as the Cervical vertebrae. It consists of seven bones namely C1 to C7 vertebrae.
11	Sacrum Angle	Angle formed by the true. Conjugate with two pieces of sacrum.
12	Scoliosis slope	Severe condition in which the spine shows a lateral shift and forms a sideway curvature.

Lin *et al* [2006], presented a paper "A Decision Support System for lower back pain diagnosis: uncertainty management and clinical evaluations". It focusses upon designing, the implementation and evaluation of an easily available framework in order to obtain the details of the patients and the relatively preferred diagnosis. The framework acted as a clinical support for LBP diagnosis and became an upholder in decision support system research [6]. Bishop *et al* [1997], designed an Artificial Neural Network (ANN) based predictive model for classification of LBP which was dependent on kinematic data. The ANN model determined certain traits of trunk linked with various types of spinal disorders and checked if it could help in deciding the effectiveness of neural work analysis system in differentiating patterns [7]. Sandag1 *et al* [2018], published a paper on the "Classification of Lower Back Pain Using K-Nearest Neighbor Algorithm" that considered on normal or abnormal lower back pain based on 12 Range of Motion (ROM). The author used K-fold cross validation method to test the data [8]. In [9], Jenkins H. presented a categorization method for the classification of low back pain. In [9], an algorithm based on heuristics and pattern recognition was developed to distinguish between lower back pain responsive to chiropractic treatment and one due to pathological causes. Gaonkar *et al* [10], published a paper on classification of lower back pain disorder using 4 different Machine Learning techniques and 6 radiographic features extracted from the data set The Paper [10], explains the research priorities of primary care medical practitioners of lower back pain and the level of importance of every parameter considered in the classification [10].

Unlike in [10], in our study we consider 11 different Machine Learning techniques and considered in one case 8 radiographic features while in another case all the 12 radiographic features contained in the dataset.

This Paper is organized as follows. Section II outlines the research objectives to be achieved in the study. Methodology used in this paper is explained in Section III. Section IV explains the results given by the proposed models and comparison among them is shown in this section. Conclusion and future work are illustrated in Section V.

II. RESEARCH OBJECTIVE

Our research objective is to generate a Non- Conventional Classification model using different Machine Learning techniques which can:

- Correctly classify Lower Back Pain symptoms either Normal or abnormal.
- Act as a Clinical Decision Support System
- Produce results with less computational time
- Help Chiropractors and Physicians in critical conditions as sometimes symptoms are too complex to classify.

III. METHODOLOGY

Methodology section for this paper is explained in 4 steps. First step explains about data gathering and preprocessing which is explained in section III.A. Section III.B depicts Model building. Section III.C illustrates the training and testing of designed models. Section III.C explains performance evaluation of the designed models.

A. Data Gathering and Pre-processing

The dataset used in the study has been retrieved from a website named "Kaggle". Attributes of the Original dataset has been assigned with labels as shown in Table III.

TABLE III: RANGE OF MOTION (ROM) ATTRIBUTES

Attribute Label	Attribute Name
Col1	Pelvic Incidence
Col2	Pelvic Tilt
Col3	Lumbar Lordosis Angle
Col4	Sacral Slope
Col5	Pelvic Radius
Col6	Degree Spondylolisthesis
Col7	Pelvic Slope
Col8	Direct Tilt
Col9	Thoracic Slope
Col10	Cervical Tilt
Col11	Sacrum Angle
Col12	Scoliosis Slope

This dataset is firstly normalized and reordered in Waikato environment [11]. Then this data is fed to feature selection method named as Automatic Feature Engineering technique to extract the most important features out of attributes. Figure shown below gives a schematic process from data gathering to feature extraction.

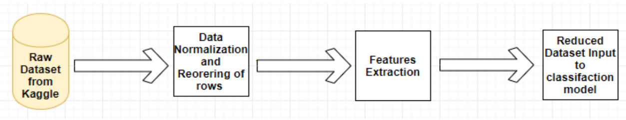

Fig. 1. Data gathering and preprocessing.

Automatic Feature Engineering technique uses multi-objective evolutionary algorithm which finds optimal Pareto set of features [12]. Featured data after application of feature extraction technique is shown below.

TABLE IV: FEATURED DATA

Col1
Col2
Col3
Col4
Col5
Col5/Col10
Col6
Sqrt (Col5/Col10)

As displayed in Table IV shown above, there are 8 featured inputs to the classifier.

B. Model Simulation

In this study, 11 classification models have been considered. All the models are generated in data mining software named Rapid miner [13]. This software provides a Graphical User Interface (GUI) for the analytical workflows or commonly termed as process. Every process consists of group of functional units called operators which are designed to perform specific tasks.

Model simulation parameters for each model are briefly explained below:

1) *Naïve Bayes' classifier*

This classifier implements Bayes' theorem for analysis. This classifier is called naïve because it assumes that all the variables are independent of each other. While constructing this classifier Laplace Correction was set to active in order to remove zero frequency [14].

2) *Logistic regression classifier*

This classifier is used exclusively for classification which is done by transforming the output between 0 and 1 using transformation called Logistic function. Coefficients of logistic regression equation is calculated by using training data [15]. Model parameters are as follows (see Table V):

TABLE V: MODEL PARAMETERS FOR LOGISTIC REGRESSION CLASSIFIER

Model Parameter	Value/Type
Optimization Algorithm	L_BFGS
Maximum Number of Threads	5
Maximum Iterations	100
Remove Collinear Columns	Activated

3) *Deep learning classifier*

The Deep Learning classifier is a type of artificial neural network with several dense layers of nodes between input and output. It adapts the training data easily provided the numbers of training samples are adequate [16]. For this study, a Fully Connected Deep Network has been modelled. Hidden layer architecture is shown in the table VI below:

TABLE VI: DEEP LEARNING HIDDEN LAYER ARCHITECTURE

Hidden Layer	Type of Layer	Number of Neurons	Activation Function
Layer 1	Fully Connected	18	RelU
Layer 2	Fully Connected	80	RelU
Layer 3	Fully Connected	2	Softmax

The Model parameters for the deep learning classifier are shown in the Table VII below.

TABLE VII: MODEL PARAMETERS FOR DEEP LEARNING CLASSIFIER

Model Parameter	Value/Type
Loss Function	Cross Entropy
No. of Epochs	1000
Type of updater	Adam
Learning rate	0.01
Weight Initialization activation	RelU
Bias initialization	0

4) *Random forest classifier*

The Random Forest classifier adapts ensemble learning algorithm. In this machine learning classifier type, Bootstrap aggregating or Bagging is used in the training algorithm [17]. Model parameters are as follows (see Table VIII):

TABLE VIII: MODEL PARAMETERS FOR RANDOM FOREST CLASSIFIER

Model Parameter	Value/Type
No. of trees	60
Criterion for optimality	Gain Ratio
Maximal Depth	7
Voting Strategy	Confidence Vote
Minimum Gain	0.05
Minimum Leaf Size	02

5) *Support vector machines classifier*

The Support Vector Machine (SVM) draws the extremes of dataset called as hyper planes. Figure shown below displays the 2D SVM classification plot [18]. Transformation from 2D SVM to 3D SVM is usually done by Kernels.

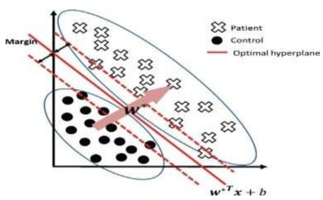

Fig. 2. SVM 2D plot.

Simulation parameters to generate SVM classifier are shown in the Table IX.

TABLE IX: MODEL PARAMETERS FOR SUPPORT VECTOR MACHINES CLASSIFIER

Model Parameter	Value/Type
SVM type	C-SVC
Kernel Type	Rbf
Gamma	1
C	100
Epsilon	0.001

6) Decision trees classifier

The Decision Trees classifier adapts supervised learning algorithm. It is usually termed as CART (Classification and Regression Trees). This classifier implements greedy algorithm and picks local minima hence it can generate complex trees which are hard to analyze [19]. Simulation parameters for this classifier are as follows (see Table X):

TABLE X: SIMULATION FOR DECISION TREES CLASSIFIER

Model Parameter	Value/Type
Criterion	Gain Ratio
Maximal Depth	4
Confidence	0.1
Minimum Gain	0.01
Minimum Leaf Size	2

7) Gradient boosted trees classifier

The Gradient Boosted Trees adapts ensemble learning algorithm where results from weak learners join together to produce more accurate results. It adapts sequential ensemble where each model is built based on correcting the misclassifications of the previous model [20].

The Parameters for GBT simulation are shown in Table XI:

TABLE XI: MODEL PARAMETERS FOR GRADIENT BOOSTED TREES CLASSIFIER

Model Parameters	Value/type
No. Of Trees	20
Maximal Depth	4
Min Rows	10
Learning Rate	0.1
Sample Rate	1
Distribution	Binomial

8) Artificial neural networks classifier

The ANN classifier is inspired by biological human neurons. It is a collection of connected units or nodes called artificial neurons. In this research, Feed forward Back propagation type ANN is used [21]. Hidden layer architecture is as follows(see Table XII):

TABLE XII: ANN HIDDEN LAYER ARCHITECTURE

Hidden Layer	Number of Neurons	Activation Function
Layer 1	8	Rectifier
Layer 2	5	Rectifier

The training parameters for ANN classifier are as follows (see Table XIII):

TABLE XIII: MODEL PARAMETERS FOR ANN CLASSIFIER

Model Parameter	Value/Type
Activation Function	Rectifier
No. of Epochs	100
Learning Method	Gradient Descent (ADADELTA)
Epsilon	e-8
Rho	0.99

9) MLP Classifier

This type of classifier is a type of Artificial Neural Network which is always feed forward and type of activation is sigmoid [22]. The considered proposed MLP classifier has 8 neurons in input layer, 18 neurons in hidden layer and 2 out layer neurons. Maximum iterations are 100 and learning algorithm is back propagation

10) K-Nearest neighbor classifier

The KNN classifier adapts lazy learning that classifies datasets based on their similarities with neighbors. 'K' stands for the neighbours near around test point and picking the popular class among them. 'K' is usually odd to avoid anomaly [22].

The Model training parameters are as follows (see Table XIV):

TABLE XIV: MODEL PARAMETERS FOR KNN CLASSIFIER

Model Parameter	Value/Type
K	5
Weighted Vote	Enabled
Measure Type	Euclidean distance

11) Fast large margin classifier

The FLM classifier is normally used for large margin optimization and provides large margins between hyper planes. This algorithm usually gets optimized by L2-SVM Dual whose objective function is to minimize the squared error [23].

TABLE XV: MODEL PARAMETERS FOR FLM CLASSIFIER

Model Parameter	Value/Type
Solver	L2 SVM Dual
C	1000
Epsilon	0.01
Bias	Activated

For each algorithm explained above (see Table XV), training parameters were tuned for maximum accuracy in testing phase.

C. Training and Testing of Proposed Models

The Dataset consists of 311 data points out of which 187 data points (60% of dataset) is used for training and 124 data points (40% of dataset) is used for testing of the proposed models. Performance of each proposed model is calculated based on the test dataset and is compared in next section.

D. Performance Evaluation

As mentioned above, performance of each classification model is evaluated by inputting test dataset and then all classifiers are compared to each other based on the values of Accuracy, Precision, F-measure, Sensitivity, Specificity and Area under Curve. The Performance parameters are defined as follows:

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

$$\text{Precision} = TP/(TP+FP)$$

$$\text{Sensitivity} = TP/(TP+FN)$$

$$\text{Specificity} = TN/(TN+FP)$$

$$\text{F-measure} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$$

[TN- True Negative, TP- True Positive, FN- False Negative, FP- False Positive] where Positive Class=

Abnormal

AUC – Area under ROC or Area under TPR-FPR curve where TPR=Sensitivity= TP/(TP+FN) and FPR= 1-Specificity= FP/(TN+FP) [TPR- True positive Rate, FPR- False Positive Rate] [24]-[26].

IV. Results

This section explains the performance of the classifiers. Based on six performance parameters explained in Section III & IV, all proposed models are compared, [26]. Comparison graphs are shown in Fig. 3:

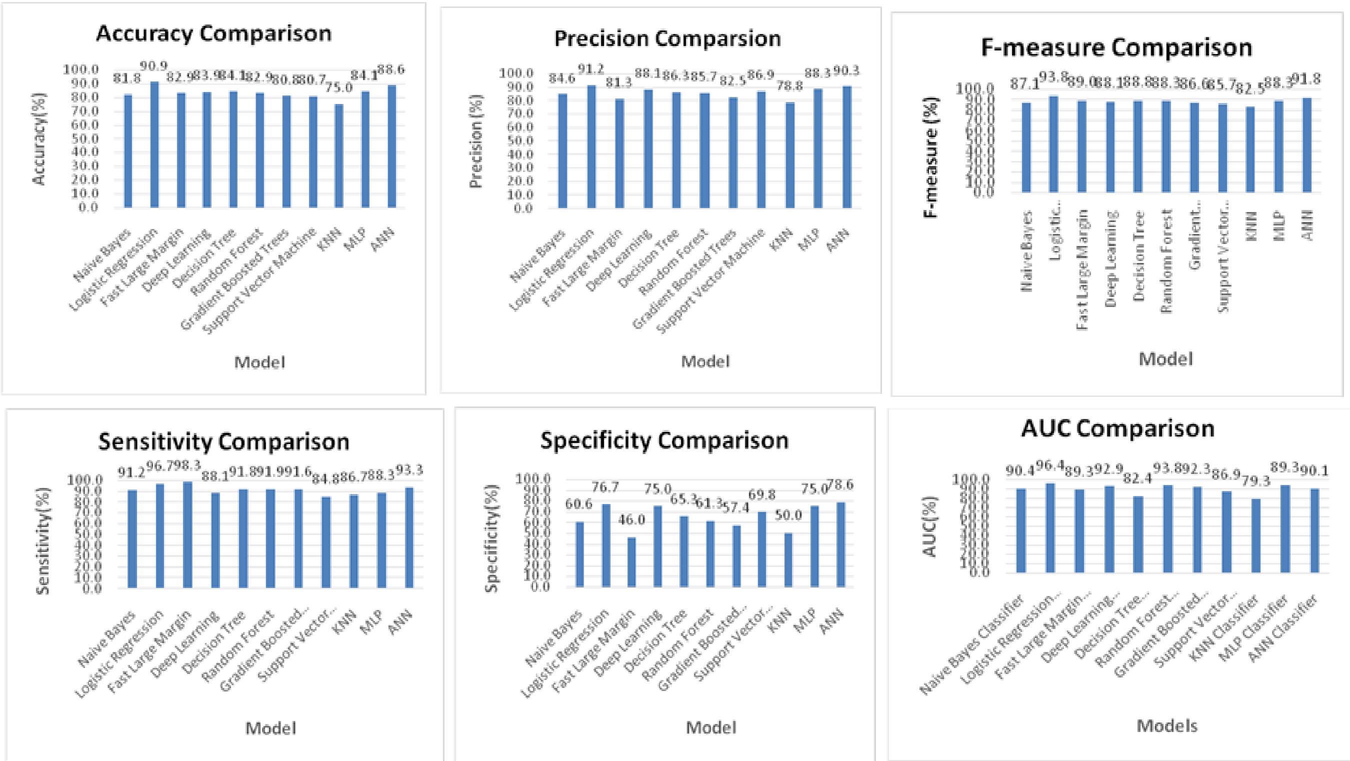

Fig. 3. Performance comparison of proposed models.

TABLE XVI: Computational Time For The Machine Learning Classifier

Model	Training Time(in sec)	Execution Time(in sec)
Naïve Bayes	0.998	0.004
Deep Learning	8.132	0.868
Decision Trees	0.59	0.01
Logistic Regression	7.162	0.851
SVM	1.932	0.125
Random Forest	8.891	0.009
Gradient Boosted Trees	45.172	0.832
Artificial Neural Networks	7.235	0.486
Fast Large Margin	0.991	0.008
Multi Layered Perceptron	1.521	0.168

As seen from the Accuracy comparison graph, Logistic Regression Classifier gives best value of accuracy (91.90%) on test dataset among all tested models. ANN classifier gives second best value (88.10%). After analyzing Precision comparison graph, Logistic Regression Classifier is most precise and ANN Classifier follows. In terms of F-measure, Logistic Regression Classifier is best among all test models. In terms of Specificity, ANN classifier gives best value among all being followed by Logistic Regression Classifier. FLM gives highest value of Sensitivity (98.3%) out of all being followed by Logistic Regression Classifier. In terms of Area under Curve, Logistic Regression Classifier give best value among other test models. Following table gives computational time of Classification models

As seen from the Table XVI, it can be observed that Decision Trees classifier is computationally fastest and Random Forest classifier takes longest computational time as compared to other machine learning based classifiers.

Weights of the Attributes are displayed with respect to proposed machine learning models in the Table XVII.

As observed from the data presented in Table XVII, Col6 or Degree Spondylolisthesis is having maximum weight among all other features. This justifies theoretical importance of this feature as it is most critical feature to detect lower back pain. From all proposed models, Logistic Regression Classifier has weight factor 0.467 for this feature which is highest and hence performance given by this classifier was best in terms of Accuracy, Precision, F-measure and Area under Curve.

The dataset used in the current research for training and testing purpose has target values which comprises of 32.5 % of the data points categorized as Normal, and 67.5% of the data points categorized as Abnormal Class. Hence, Accuracy can be considered as a crucial metric to compare model performance.

In order to verify the significance of feature extraction and feature engineering on the current dataset, a comparison has been done to check model performance while feeding only featured data in first case and all data was fed in other case. The following table, illustrates the results obtained:

TABLE XVII: WEIGHT OF ATTRIBUTES FOR THE MACHINE LEARNING CLASSIFIERS

Sr.No.	Featured Input Data	Classification Model										
		Naïve Bayes	Deep Learning	Decision Trees	Logistic Regression	SVM	Random Forest	ANN	MLP	KNN Classifier	Fast Large Margin	Gradient Boosted Trees
1	Col1	0.044	0.018	0.041	0.043	0.026	0.047	0.017	0.033	0.049	0.026	0.011
2	Col2	0.052	0.089	0.038	0.128	0.025	0.123	0.108	0.076	0.025	0.062	0.077
3	Col3	0.079	0.027	0.022	0.022	0.035	0.044	0.028	0.02	0.014	0.023	0.022
4	Col4	0.045	0.063	0.035	0.042	0.019	0.03	0.067	0.042	0.008	0.019	0.059
5	Col5	0.007	0.05	0.009	0.029	0.012	0.041	0.041	0.028	0.007	0.019	0.03
6	Col5/Col10	0.044	0.082	0.114	0.107	0.006	0.134	0.055	0.055	0.228	0.474	0.038
7	Col6	0.168	0.449	0.207	0.467	0.106	0.356	0.45	0.434	0.057	0.219	0.415
8	sqrt(Col5/Col10)	0.033	0.007	0.019	0.07	0.037	0.035	0.039	0.005	0.052	0.133	0.018

TABLE XVIII: COMPARISON OF ACCURACIES WITH FEATURES AS COMPARED TO TOTAL ATTRIBUTES

Model	Accuracy (With 8 features)	Accuracy (with all 12 attributes)
Naïve Bayes	81.8	85.23
Deep Learning	83.87	77.43
Decision Trees	84.1	83.15
Logistic Regression	90.91	84.09
SVM	80.7	79.36
Random Forest	82.9	87.5
Gradient Boosted Trees	80.8	80.09
Artificial Neural Networks	88.6	83.15
Fast Large Margin	82.9	81.21
Multi Layered Perceptron	84.1	79.55

As seen from the Table XVIII, the best accuracy that can be achieved by any model is Logistic Regression classifier when it is subjected to featured data. Naïve Bayes and random forest classifiers give higher accuracy considering the total attributes; but still it is not able to surpass the accuracy given by logistic regression classifier with featured data.

V. CONCLUSIONS AND FUTURE WORK

This study provides a Non-Conventional Approach to detect Lower Back Pain in Human Body. Machine Learning and Intelligent Systems techniques can be used as clinical decision support systems which can support doctor's decision especially at critical cases. The Logistic Regression Classifier was used and tested which gives an accuracy of 90.91% on the test data and hence considered as the most accurate method among all methods used in this research. Apart from accuracy, if precision, F-measure and AUC are taken into consideration, the Logistic Regression based model is the "best" model among other test models. In terms of Sensitivity, the Fast Large Margin model is suited as the "best" and Logistic Regression is second "best". The Artificial Neural Network based Classification model gives the "best" result as compared to others in case of Specificity (78.6%).

Only 311 data samples are publicly available on-line to do the training as well as testing. For improved performance of models, additional data may be required. This paper presents a systematic approach to use Non-Conventional classification techniques to classify LBP data. Still an effort can be made on the current models by changing model parameters, different features selection methods and data pre-processing to get better accuracy. The global minima for back propagation of the ANN, Multilayer Perceptron, and the Deep Learning Models can be considered and the performance of these models can be evaluated. Researchers are encouraged to use others frameworks that use a variety of parameters for Machine learning algorithm implementation.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS CONTRIBUTION

Shubham Sharma: Conceptualization, Formal Analysis, Methodology, Investigation, Writing-original Draft. Dr. Rene V. Mayorga: Formal Analysis, Methodology, Supervision, Paper Review & Editing, Funding Acquisition.

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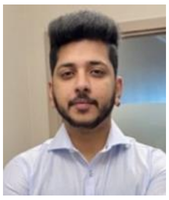

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