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Machine Learning Algorithms for Clinical Diagnosis of Lower Back Pain – A Survey

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ABSTRACT

Lower back pain due to spinal abnormality causes severe disability in 80% of all age population globally. The primary cause of lower back pain is injuries in bones, joints, ligaments, muscles and spinal cord, leading to spinal abnormalities. LBP may also occur in persons with lifestyle changes, improper sitting position, sitting within the same position for a longer time cause an uncomfortable condition in the spine. However, it is often difficult to discriminate the intensity of pain to an abnormal condition. The advancement in artificial intelligence and machine learning techniques helped diagnose low back pain by analysing the clinical diagnostic information of a patient. An appropriate feature selection technique is used to identify significant features for the classification process. The severity of the spinal disorder or abnormalities in lower back pain patients can be diagnosed with Machine learning algorithms. These algorithms are used to classify spinal abnormality in a dataset with 310 patients retrieved from Kaggle repository. This article mainly presents various literary works that have used machine learning algorithms to classify lower back pain in patients with spinal abnormalities.

Keywords: Machine learning algorithms, lower back pain, classification, feature selection, clinical diagnosis.

Introduction

The spine is the fundamental support system of the human body. With the quick advancement of computational knowledge, analysts consider the forecast of various sicknesses from clinical information acquired from the patients [1],-[3]. As low back pain, turning out to be a deadly worldwide issue, artificial intelligence (AI) and machine learning techniques are used by specialists to recognize patients with lumbar spine problem with theirs spinal area information. Lower back pain (LBP) occurs in patients due to several complications affecting approximately 80% of the world population. LBP is considered one of the physical disability of a person in the lower part of the spine structure affecting the regular physical activities of a person engaging in work. At the initial stages, patients will try home remedies like pain relief cream, sleep, reduce stress, exercise, use heat and cold packs, stretch the body for faster back pain relief [4]-6].

The lower back pain in a person is greatly influenced by lifestyle changes, accidents, occupational and workplace parameters, and psychological factors. The various reasons for lower back pain may be irritation, strain, ligaments sprain, or damage in the discs, bones and joints of a human body [7] - [9]. The injury in a spine structure mainly affects the lumbar spine, discs between the vertebrates, muscle, spinal cord, and ligaments that become chronic, resulting in the degeneration of various parts of the body [10]. Lower back pain can be categorized into Spondylosis, Spondylolisthesis, disc hernia, and lumbar spinal stenoses are the few to mention.

The lower back pain in the lumbar spine is associated with various attributes like pelvic incidence, pelvic tilt, sacral slope, and so on. Identifying lower back pain in patients having spinal abnormalities has gained importance in recent years for earlier diagnosis and treatment of these patients [16]-[18]. Numerous researches have reported applying artificial intelligence/ machine-learning algorithms for medical diagnosis and classification of diseases [13], [14], [15], [19]. The AI/ML techniques help identify and classify diseases in a patient such as cancer, cardiovascular disease [10], chronic kidney disease [11], lower back pain [12], and classify them into normal and abnormal cases.

The rest of the paper is structured as follows. Section 2 gives technical details about the machine learning algorithms, database description, data portioning and importance of feature selection. Section 3 presents the review of the related works in the literature with the state-of-the-art techniques used in the diagnosis and classification of Lower back pain. Section 4 concludes this study and gives scope for future directions.

2. Technical Background

1. Machine Learning Algorithms

Machine learning algorithms are widely used to improve the diagnosis, prognosis and classification of chronic diseases [21]. These algorithms can recognise patterns in the data and successfully classify an individual as diseased or healthy [26]. ML algorithms are used in the diagnosis of lower back pain in patients having spinal abnormalities [32], [34]. This section discusses the widely used classifier models for the diagnosis and classification of LBP.

(a) K-Nearest Neighbour (K-NN)

The K-Nearest Neighbour algorithm is the most learning algorithm based on the supervised learning methodology used in Data Mining algorithms. The K-NN algorithm is a statistical non-parametric classification method that is used for the classification and regression process [35]. The algorithm assumes it classifies the new data by computing the distance between the new features with the existing cases. Whenever new data is received, the algorithm classifies the new data close to the group having the most similar samples according to its k number of nearest neighbours. The distance function used in KNN is the Euclidean distance measure.

(b) Support Vector Machine (SVM)

The Support Vector Machine is a popular supervised learning algorithm used for classification and prediction, and it is widely applied for binary classification purposes. The Support vector machine algorithm uses a non-linear mapping to determine the high dimensional feature space boundary for categorising N-dimensional data. The SVM algorithm searches for an optimal hyper-plane to separate data belonging to different classes. The support vectors in SVM are the vectors that assist and define the hyper-plane's location. During the classification process, the data samples are classified into appropriate classes based on the hyper-plane position [35].

(c) Classification and Regression Tree (CART)

The classification and regression trees (CART) are supervised learning algorithms that implement the Decision Tree used for the classification and regression process [35]. The decision tree algorithm starts with the root node branching into several non-leaf internal nodes with leaf nodes or terminal nodes. The internal node represents a single input variable,

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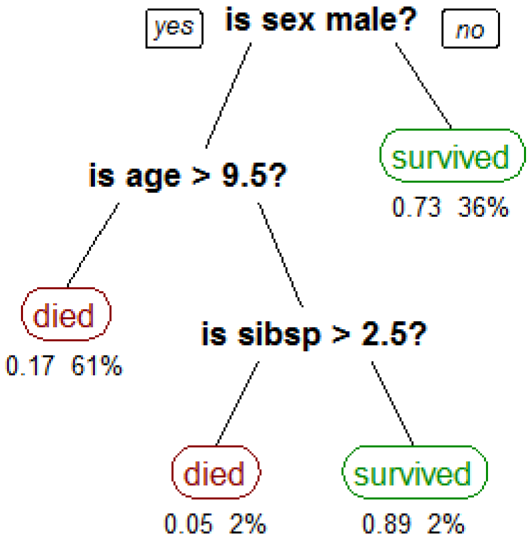
and the leaf node represents the class label or output variable. For splitting any interior nodes into sub-branches, the algorithm uses the Gini index and gain ratio. The tree constructed is used to make a prediction. Class labels represent data attributes, and nodes reflect deciding laws and each data point to the outcome in this tree-structured algorithm. The observations or evaluations are made depending on the types of the specified data.



(d) Random Forest (RF)

Random Forest is an ensemble machine learning algorithm that uses the supervised approach [36]. In machine learning, it is used for both regression and classification problems. This ensemble method randomly finds the root node to create several decision trees that split the nodes and then combine the decision trees' classification result to predict the class for increasing the model accuracy correctly. The algorithm uses Gain Ratio, or Gini Index, for splitting operation. The random forest algorithm can also be used as an embedded feature selection method for selecting the most significant features for training.

2. Database description

The dataset used in this research is retrieved from the Kaggle repository [38]. The data consists of 310 patient records having two categories, namely normal and diseased. The data contains only numerical attributes related to biomechanical characteristics and do not have demographic features. These attributes are necessarily correlated with all of the attributes. The data comprises 310 patient records categorized into two groups, with 210 persons are patients or having lower back pain and 100 persons are normal. Every patient record is unique, consisting of 12 biomechanical features and one class attribute. The physical parameters or attributes associated with the lower back pain used for identifying spinal abnormalities are pelvic incidence, pelvic radius, lumbar lordosis angle, sacrum angle, pelvic tilt, direct tilt, cervical tilt, sacral slope, thoracic slope, scoliosis slope and degree spondylolisthesis. The details about the range of each attribute are given in Table I.

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Table I – Feature attributes Information with its Range

Attribute Name	Type	MIN value	MAX value
Pelvic incidence	Numeric	26.1	130
Pelvic tilt	Numeric	-6.5	49.4
Lumbar lordosis angle	Numeric	14	126
Sacral scope	Numeric	13.4	121
Pelvic radius	Numeric	70.1	163
Degree spondylolisthesis	Numeric	-11.1	419
Pelvic slope	Numeric	0	1
Direct tilt	Numeric	7.03	36.3
Thoracic slope	Numeric	7.04	19.3
Cervical tilt	Numeric	7.03	16.8

3. Dataset Partition

The dataset partition is a complex process as it dramatically affects the performance results, and even it becomes more challenging when the dataset is highly imbalanced [22]. The dataset can be partitioned using a hold-out method or using K-fold cross-validation techniques. In the hold-out partition, the dataset is divided into training and testing set. The training set is used to train the classifier model, whereas the test set is used to evaluate the model performance. In K-fold cross-validation, the dataset is divided into K folds where a proportionate amount of each class is used in different folds. During the model training and evaluation, K-1 folds are used to train the classifier model, and one fold is used to validate the model's performance. This process is repeated for all the folds K times, and the average is taken as the result to estimate the classifier's performance.

4. Feature Selection

Feature selection is choosing some informative and relevant features from a large dataset that provides better characterization of patterns of multiple categories for both classification and regression tasks. There are different Feature selection measures for selecting relevant features, and they can widely be categorized into three types: filtering-based method, wrapper-based methods, and embedded strategies. Filter techniques are statistical methods that are quicker compared to other feature selection strategies. In a filter-based technique, each feature is evaluated one at a time instead of estimating several attributes alone. Moreover, filter-based feature selection algorithms are highly scalable that can be used for selecting relevant features in high-dimensional datasets, which is relatively easy and economical for any classification algorithms. One of the widely used filtering based approaches is the univariate feature selection methodology that considers every feature relevancy with the target variable [29]. In this method, every feature is scored on an individual basis based on specific criteria. Therefore, those chosen features are based on feature importance and have higher scores for a feature.

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3. Review of Literature Works.

This section presents a list of previous literature works that have used machine learning algorithms to identify and classify lower back pain in patients with spinal problems. The authors in [20] have presented their work to assess the patients having chronic lower back pain using a support vector machine (SVM). An appropriate feature selection algorithm is used to select the significant parameters for diagnosis and classification of spinal abnormalities using the Spinal 3D kinematic assessment method. The authors have used five features to predict the spinal abnormalities and achieved a classification accuracy of 100% with a support vector machine. The author [23] proposed an ANN model to classify lower back pain by selecting the required parameters from dynamic motion characteristics of trunk motion and movement velocity. The neural network algorithms achieved a classification accuracy of 86% in predicting the disease using kinematic data.

An ANN classifier model for predicting chronic lower back pain detection is employed in [24], [30] using the Electromyography data of para-spinal muscles. A nonlinear analysis is used for LBP detection and achieved an accuracy of 80% using the ANN algorithm. The study presented in [25] utilized ANN, Logistic Regression, K-NN for predicting lower back pain in a group of industrial workers based on the features related to personal, psychological and occupational factors. A total of fourteen feature attributes are selected to predict the spinal abnormalities in a person. The K-NN algorithm achieved a higher predictive accuracy of 92% when compared with other algorithms. In research carried out by the authors in [27], Deep learning is used to identify low-back pain with statistical measures [37]. The three essential features, namely Angular rotation, the centre of pressure measures and linear translation, are used to train the ANN and Deep learning neural networks. An accuracy of 97% is achieved with the ANN algorithm.

The authors in [28] used Principal Component Analysis (PCA) to select significant features and applied ANN for classifying spinal abnormalities. The prediction utilized the attributes based on the lifting capacity evaluation of a person. Classification accuracy of 0.89% is achieved with Artificial Neural Network. The study in [31] utilized different sitting posture measures for predicting lower back pain using the Support Vector Machine. The pressure sensor is used to acquire the stress while a person is in the sitting position. The classification accuracy of 100% is achieved in predicting the LBP with the SVM algorithm. The authors in [33] employed ANN for selecting relevant feature for the prediction of lower back pain. They achieved a classification accuracy of 91% with Artificial Neural Network. The authors in [39] predict lower back pain based on the pain level. The SVM classification algorithm is trained with the Trunk flexion kinematics, muscle lobe, EMG, sit-to-stand kinematics, and depression features for predicting lower back pain. The algorithm achieved 94% classification accuracy in identifying patients with chronic LBP.

The Electromyography data is utilized for predicting lower back pain in patients in [40]. The author employed ANN to classify electromyography signals for identifying back pain in patients and achieved a classification accuracy of 0.92% with the ANN algorithm. A K-Means Clustering and self-organizing map (SOM) algorithms are applied in [41] to categorize data for diagnosing spinal pathology and predict lower back pain. The authors used six features to predict lower back pain with ANN and achieved a classification accuracy of 0.83% with the Artificial Neural Network algorithm. The author in [42] used SVM for selecting significant features from Electromyography data for predicting lower back pain. The surface electromyography is used to detect chronic lower back pain by applying SVM models to get high accuracy in predicting chronic low-back pain.

The authors in [43] selected the gait features for the classification of LBP. These features are collected using a smart-phone to identify people with lower back pain. Machine learning algorithms like ANN, MLP, Decision Tree are used to classify LBP using the gait features. The DT model outperformed other algorithms and achieved 88% classification accuracy to detect patients with LBP correctly. A study presented in [44] utilized Electromyography data for predicting spinal abnormalities in patients. The authors have employed suitable feature selection measure for significant feature selection. The Naive Bayes classifier model is used to identify chronic lower back pain and achieved an accuracy of 70%. The authors in [45] studied the performance of different machine learning algorithms like K-NN, MLP and Radial Basis Function (RBF) for the classification of lower back pain. The feature selection algorithm is used to choose relevant feature attributes associated with the spinal disorder. The K-NN algorithm outperformed other algorithms and achieved 95% classification accuracy in predicting lower back pain in patients.

4. Conclusion

This study discusses the various indications that remain undetectable in the initial phases of Spinal abnormalities, which is a significant health concern in all populations, especially in the ageing population having spinal abnormalities requiring special care and attention. The lower back pain may happen in everyday life for a person while undertaking regular duties, irrespective of age. The identification and classification of spinal abnormalities in a person with lower back pain utilized a machine learning algorithm. The model learns from the training dataset, and its performance is evaluated with a testing dataset. The performance evaluations of any classifier models are assessed in terms of classification accuracy, sensitivity, specificity, precision and F1 score. This survey article will help researchers develop algorithms based on deep learning models and hybrid ensemble methods for identifying LBP using the dataset retrieved from the Kaggle repository.

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