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Early Detection of Low Back Pain: A Machine Learning Approach with Enhanced Data Techniques

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ABSTRACT

Low back pain is a condition quite common to millions across the globe, usually leading to a high degree of disability and poor quality of living. It may result from posture faults, some deformities of the spine, injuries, or degenerative ailments. Worldwide, it leads to high healthcare and economic hindrances. Most people with low back pain have spinal deformities, such as deviations in pelvic tilt and lumbar angles, which may help in early detection and intervention. It is that acute detection would avert chronic complications, alleviation of pain, as well as improvement of the outcome of the patient. In this research, we intend to investigate the application of multiple machine-learning techniques toward early identification of LBP. We used a Kaggle dataset having 310 instances with 12 numeric attributes indicating spinal anomalies for addressing intrinsic class imbalance by SMOTE creation of more instances for the minority class. Moreover, to improve the robustness and diversity of the dataset, we adopted the bootstrapped resampling method to add reliability into model training by replicating those data points. Advanced machine learning models were trained on this enhanced dataset, and their performances were evaluated rigorously. Advanced Gradient Boosting model was exceptionally capable, overtaking the other techniques and those of previous research with perfect accuracy of 1.00. Each model underwent systematic fine-tuning to optimize its performance further, ensuring reliable and actionable results. This research comes as an excellent contribution to the field of LBP detection by providing strong and effective protocol which could change healing practice from one type of diagnosis and treatment to another.

INTRODUCTION

Lower back pain, a common musculoskeletal condition that affects people across the world(Chen, Chen et al. 2022). In severe conditions, LBP is disabling. It is multifactorial, having causes such as, disc degeneration, mechanical stresses, muscle imbalances, psychosocial(Organization 2018) factors, and others. This issue is also a challenge since the causes it is built upon have co-morbidity of LBP (Haider, Hashmi et al. 2024) and a complex biopsychosocial nature and structuralism with regard to LBP in its socio-political contexts affecting daily functioning(Grabovac and Dorner 2019).

These opportunities often come under broadly stated causes including lack of jobs (Chowdhury, Huda et al. 2023), poor productivity of work providers, and emotional distress. Together with regular time to sleep(Alsaadi, McAuley et al. 2014) and the chance of using regulatory medication, the everyday quality of life(Agnus Tom, Rajkumar et al. 2022) is still low. Instead, even higher probabilities of disability(Stefane, Santos et al. 2013) that mean it would be even more difficult to do these tasks in the future support the same. Costs for complementary interventions or treatments that LBP-affected people pay are paid. Certainly, all medical conditions and added costs will be highlighted.

Low back pain (LBP) accounts for roughly 619 million cases worldwide, making it the leading cause of global disabilities. This condition not only incapacitates individuals but also imposes significant societal (Mathew, Singh et al. 2013)and economic costs. However, it does not address a critical issue that, if resolved, could eliminate a significant portion of employment altogether. LBP patients often experience agony (Pinto, Neves et al. 2023) that is primarily reflected through functional impairments, from top to bottom, affecting their overall well-being. The associated costs are enormous, and society continues to bear this burden (Fatoye, Gebrye et al. 2023). From a back-specific perspective, the effects of LBP are among the central consequences of this condition.

Machine learning in healthcare (Sarker 2024) has revolutionized the field by analyzing big data patterns from numerous individuals to create tailored treatment recommendations automatically (Gill, Saeed et al. 2023) and predict the onset of infections. While healthcare administration has become quicker and more efficient, there is still a delay in diagnosis. Machine learning performs exceptionally well in addressing some of the most challenging problems in medicine and introduces new insights into precision, timeliness, and personalized treatment. Its quick and reliable methods for predicting disease and identifying dependencies enhance its effectiveness. This demonstrates that using (Kasula 2021) machine learning in innovative healthcare applications is cost-effective, as it eliminates many human errors, much like other automation technologies.

In prediction tasks, machine learning-based methods achieve high accuracy compared to manual detection, which is more susceptible to human error. The consistent and uniform behavior of machine learning in medical detection (An, Rahman et al. 2023) helps avoid critical oversights, ensuring reliability and alignment with the intended tasks. This makes machine learning highly effective for such applications. Therefore, if all capabilities are properly understood and applied within the governance of machine learning in healthcare (Rubinger, Gazendam et al. 2023), the potential benefits could be substantial (Javaid, Haleem et al. 2022).

LITERATURE REVIEW

In recent years, significant progress has been made in the field of lumbar spine disease detection, particularly through the integration of machine learning techniques. Numerous studies have explored various models and algorithms, enhancing our ability to diagnose and classify spinal conditions with greater accuracy and efficiency. This review aims to synthesize the key findings from these studies, highlighting the advancements and ongoing challenges in this area. Previous work is presented in Table 1.

This research (Singh, Singla et al. 2023) concentrates more on optimizing a spider monkey-based feature extraction approach and through a linearity-based CNN structure for better classification. MRI data were retrieved from hospitals endorsed by a medical authority, blameless of misclassification and highest classification accuracy with lower misclassification. Multiple classifiers-Multi Support Vector Machine, Random Forest, Decision Tree, and Naïve Bayes-were employed, and it was discovered that MSVM scored 96% in terms of accuracy. However, the developed procedure apparently improved significantly in classification accuracy, specificity, sensitivity, and F-Score metrics with extensive validation beyond the earlier method.

The Study(Islam, Asaduzzaman et al. 2019) reveals a study on application of machine learning techniques for the low back pain (LBP) classification. It must be made known that the dataset used was from a sample of 310 patients with 12 features, and the implemented models were Logistic Regression, Decision Tree, Naive Bayes, and Random Forest. The most accurate result using this data is achieved when the Random Forest classifier is applied, since reached an accuracy value equal to 94%. It proves the significance of the feature optimization through evolutionary feature elimination, mainly useful concerning identifying which attributes.

The research (Shim, Ryu et al. 2021) delves into machine learning models that predict chronic lower back pain (LBP) among the elderly. Data were taken from the Korea National Health and Nutrition Examination Survey, focusing on the segment of the population aged 50-89. Eight machine learning models are developed and compared logistically regression, k-nearest neighbors, naïve Bayes, decision tree, random forest, gradient boosting machine, support vector machine, and the artificial neural network (ANN) among others. The ANN model exhibited the highest predictive accuracy with AUROC equals 0.716. With these facts and opportunities, the study can provide recognition of machine learning usage in identifying high-risk populations for chronic LBP and its targeted preventive and treatment strategies.

The study (Lamichhane, Jayasekera et al. 2021) aims to think of neuroimaging of the brain as identifying biomarkers in chronic low back pain (LBP). Chronic LBP is one of the health issues often associated with high levels of disability and huge economic costs. Conventional spinal imaging often does not assist in demonstrating the relevant central mechanisms for pain and, thus, has presented imprecise treatments. The aspects of this research are the cerebral cortical thickness (CT) and resting-state functional connectivity (rsFC) as possible biomarkers. There were found CT and rsFC apparently distinct in patients with LBP and healthy controls using structural MRI and rsfMRI data, in part associated with networks involved in pain processing and emotion. A trained support vector machine using CT data achieved a classification accuracy of 74.51%. This value suggested possible use of CT and rsFC in directing more efficacious LBP intervention modalities. Therefore, the revealed findings underline the importance of brain imaging for understanding and treating chronic LBP.

Table 1
Summary of Literature review.

Year	References	Technique	Accuracy	Dataset
2023	[33]	CNN with Spider Monkey Optimization	96%	MRI dataset from hospitals
2019	[20]	Random Forest	94%	Dataset of 310 patients with 12 features
2021	[32]	ANN	AUROC of 0.716	Data from the Korea National Health and Nutrition Examination Survey (aged 50-89)
2021	[24]	Support Vector Machine	74.51 %	Structural MRI and rsfMRI data from LBP patients and healthy controls
2019	[37]	Neural Network (Three-layer)	Over 80%	Dataset by Dr. Henrique da Mota including normal, Disk Hernia, and Spondylolisthesis categories
2020	[2]	SVM	75%	Data from 94 male NSLBP patients using inertial measurement units (IMUs)
2017	[15]	J48 Decision Tree	90.30 %	Physical spine data of 381 patients with 12 parameters
2018	[27]	Boosted Tree	72%	Dataset of 1288 fictive cases of LBP judged by physiotherapists and general practitioners
2024	[18]	RGXE Ensemble	99%	Dataset taken from Kaggle

This research (Wang, Verba et al. 2019)elaborates the prediction of spinal diseases through neural networks and underlines the point of early diagnosis keeping in view how common the back pain becomes in society. It also discusses applicability of backpropagation algorithm to make predictions for the biomechanical attributes like pelvic incidence, pelvic tilt, and lumbar lordosis angle in the view of prediction of spinal conditions. The study makes use of data set created by Dr. Henrique da Mota which included data of patients categorized under normal, Disk Hernia or Spondylolisthesis categories. The authors propose a neural network architecture in 3 layer format having an accuracy of more than 80% in tests. The authors mention further improvements that can be made using more advanced neural networks on larger databases.

This study (Abdollahi, Ashouri et al. 2020) proposes a sensor-based machine learning model to classify patients with nonspecific low back pain (NSLBP) into different subgroups based on the kinematic assessment of trunk motion and balance-related measures along with the STarT Back Screening Tool (SBST). The patients were all male NSLBPs, n = 94, who performed trunk flexion and extension while IMU wearing for text collection. Ground truth SBST scores were considered for classification purposes using the Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) algorithms. The SVM model had an accuracy of about 75%, while the MLP model achieved approximately 60%, illustrating the promise of wearable systems in developing evaluation methods for NSLBP.

In this study, a (Gaonkar, Kulkarni et al. 2017) research is proposed for classification of lower back pain disorder using various methods of machine learning empowering the assessment of significance of every single parameter. The database presented contains physical spine information of 381 patients with 12 parameters. This methodology makes use of Principal Component Analysis (PCA) for feature selection and outlier detection. The supervised techniques involving k-nearest neighbor (k-NN), Support Vector Machine (SVM), and Random Forest are used for classification. The results showed that the most significant parameter is the amount of spondylolisthesis accounted for and between Random Forest, which gives an accuracy of 87.09%, and J48 Decision Tree, which reports the most accurate result of 90.30%. This study indicates the way through which machine learning brings the opportunity for a preventive way regarding the classification of lower back pain disorders and aids healthcare practitioners in clinical treatment.

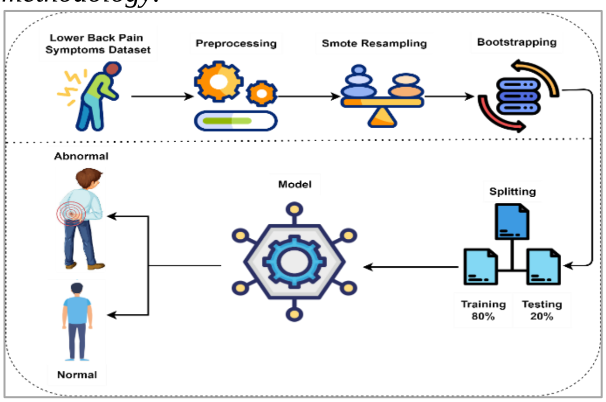
This study (Nijeweme-d'Hollosy, van Velsen et al. 2018) proposes the development of a clinical decision support system (CDSS) to assist patients with low back pain (LBP) in their self-referral to primary care. This dataset includes 1288 imaginary cases of LBP, judged by 63 physiotherapists and general practitioners (GPs) on advice to refer them. The methodology is that of supervised machine learning applied to the generation of three classification models: decision tree, random forest, and boosted tree. The models were trained on 70% of the dataset and validated with 30%. Results showed that the boosted tree is the most effective, performing with 72% accuracy in validation and 71% during testing with actual cases-suggesting its viability for real-life application in aiding self-referral decisions for LBP patients.

In this study (Haider, Hashmi et al. 2024) proposes an ensemble learning approach for Lower Back Pain (LBP) Detection with data balancing and bootstrapping techniques. It consists of a dataset of 310 patient records with spinal anomaly-related features. The proposed Random Forest Gradient Boosting XGBoost Ensemble (RGXE) incorporates Random Forest, Gradient Boosting, and XGBoost algorithms altogether. RGXE method has achieved a high accuracy rate of 99%. Data balancing takes care of the class imbalance present in the database. The bootstrapping technique was employed to bolster model stability and generalization.

MATERIALS AND METHODS

Our Research methodology for detecting lower back pain is shown in Figure 1. The first activity in the study involved collection of the dataset from Kaggle and thorough preprocessing to maintain data integrity caused by the removal of null values that would interfere with the analysis. Class imbalance was tackled through application of the Synthetic Minority Over-sampling Technique (SMOTE) (Ijaz, Alfian et al. 2018) to produce synthetic samples for the minority class, thus achieving class independence. To add on robustness, we carried out bootstrapping, a resampling technique which uses replacement in generating new observations, thereby increasing the numbers of data for model reliability. The resultant dataset was then divided into training and test data in 70:30 ratios so that they could then be prepared for training and evaluation of the model. A model trained on processed data was used to predict low back pain, and the performance was evaluated using the test set. This all-encompassing approach consists of detail-oriented data preparation, as well as intensive testing of models to ensure predictive returns are both trustworthy and actionable.

Figure 1
The structure of our innovative research methodology.



Dataset

The dataset has been taken from Kaggle (2016) that it amounts to 310 rows and contains twelve numeric feature columns plus a classification column that classifies a condition either as Abnormal or Normal. The attributes included are spinal and pelvic measurements, such as pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, and degree of spondylolisthesis. Some further attributes are pelvic slope, direct tilt, thoracic slope, cervical tilt, sacrum angle, and scoliosis slope. All these readings are important for predicting and classifying pain in the lower back, giving enough ground for training and testing models predicting spinal abnormalities. The detailed and well-balanced attributes in the dataset make it powerful for modeling with promising predictions in health care and orthopedics.

Data Balancing

Considering the dataset is imbalanced where 210 rows are Abnormal and 100 rows Normal, it is important to make the dataset balanced, as it would lead to more enhanced predictive modeling. The imbalance is now corrected by Synthetic Minority Over-sampling Technique (SMOTE) (SMOTE) (Ijaz, Alfian et al. 2018). This method works by creating synthetic samples for the minority class (in the current case, the Normal class) so that the two classes would be uniform. Such balancing with SMOTE (Ryan, Katarina et al. 2023 could make it possible for a model to learn about predicting outcomes accurately without bias towards the majority class. This preprocessing step is necessary for improving the reliability and performance of our predictive model identifying lower back pain accurately.

Data Sampling

Once SMOTE has been applied, we will then bootstrap the dataset to give it additional vigor. Bootstrapping (Yagin, Alkhateeb et al. 2023) is resampling with replacement to yield new samples from existing data. This is where we will be able to increase the dataset size for more samples and varied diversity and representation of sample for machine learning learning. Thus, once we have a number of bootstrapped datasets (Haider, Hashmi et al. 2024), the model is less likely to overfit and more likely learn to generalize from new, unseen data. The further augmenting step is critical for the development of a predictive model for the classification of lower back pain.

Data Splitting

SMOTE and bootstrapping improved the dataset, and so, now we have to proceed to data splitting for training and testing purposes. We will use 80% of the data for training purposes and 20% for performance testing of the model. With this kind of split, we succeed in making the model learn from enough data as well as a separate part of it for assessing prediction accuracy and generalizability. This creates an enabling environment to sufficiently train a strong machine learning model on lower back pain and evaluate its performance on unseen data.

Machine Learning Models

Machine learning (Haider, Hashmi et al. 2024) offers a variety of algorithms tailored for different tasks, each with its unique strengths and applications. From simple, interpretable models to advanced, high-performing methods, the choice of algorithm depends on the dataset and the problem at hand. Below, we explore some of the most widely used algorithms for classification and regression, highlighting their key characteristics and use cases.

Decision Tree (DT)
The algorithm of Decision Tree (Ahmed, Ahmed et al. 2023) is one of the largest models to classify and regress tasks. It splits data recursively into several classes based on the value of input features, creating a tree-like structure of decisions. An internal node would exist to make a decision about a single feature, and a leaf node would represent an output label or class. One of the main advantages of DT (Sun, Wang et al. 2024) is their interpretability, since the resulting tree can be visualized very easily and understood by humans. But, they can be overfitting issues, especially for noisy data.

Xtreme Gradient Boosting (XGB)
XGBoost, (Esmaeili-Falak and Benemaran 2024) is an implementation of gradient-boosted decision trees designed for speed and perfor-mance. It is very efficient when performing the task of classification and regression. An ensemble of decision trees is created sequentially by this algorithm in a way that each subsequently added tree corrects its predecessor errors. Next, XGB models (Benemaran 2023) through a combination of gradient descent and regularization techniques ensure prevention of overfitting and increase generalization. Furthermore, it works wonder on large datasets and complex models, making it the most probable candidate for machine learning competitions.

Random Forest (RF)
Random Forest (Naseer and Jalal 2023) is an ensemble learning method that constructs multiple decision trees during the training and outputs the mode of their predictions for the classification tasks or the mean prediction in case of regression tasks. This is the combined method of bagging-"Bootstrap Aggregating"-and random feature selection to construct a rich set of trees, thereby reducing overfitting and improving the robustness and accuracy of the model. RF (Karabadji, Korba et al. 2023) are usually a great candidate because of their expected high performance and multi-task versatility when handling a large number of input features.

K-Nearest Neighbors (KNN)
K nearest neighbor (Dolesi, Steinbach et al. 2024) is a simple and non-parametric algorithm for use in classification and regression. It holds that k-number of nearest neighbors are found for a given query point and then predictions are formed by the majority class or by the average of these k-nearest neighbors. KNN (Tang, Chang et al. 2023) is very intuitive and is easy to implement. However, performance is heavily dependent on the parameter k and the distance metric. It also turns out to be very expensive for large datasets with respect to computation burden as every point of such a dataset has to complete a distance calculation for every prediction.

Gradient Boosting (GB)
Gradient boosting (Arslan, Mubeen et al. 2024) is another ensemble technique for learning, whereby a number of weak learning models - usually decision trees - are fitted in sequence. Each tree works on decreasing the errors yielded by previous trees. The function of the model is to increasingly improve performance. The algorithm defines the loss function via gradient descent, making it very vital for both classification and regression tasks. GB models (Al-Haddad, Jaber et al. 2024) achieve accuracy levels that will allow them to handle quite complicated data. These models, however, tend to overfit-the result of mean squaring errors-on an average, they do not overfit unless regularization has been put properly in place.

RESULTS

The results show a considerable increase in the model performance after applying a bootstrapping method to the dataset in Table 2. The resampling-induced augmentation provided the machine learning models with the training sets that were better and diverse in its sampling location, thus boosting predictive accuracy. Specifically, Gradient Boosting (GB) achieved perfect accuracy (1.00) after bootstrapping, indicating how powerful it can be in optimal use of the enriched dataset. Equally, Random Forest (RF) and Xtreme Gradient Boosting (XGB) performed equally well with accuracies of 0.98 and opened doors to the robustness and generalization capabilities with improved data.

Before bootstrapping, K-Nearest Neighbors (KNN), Decision Tree (DT), and Gradient

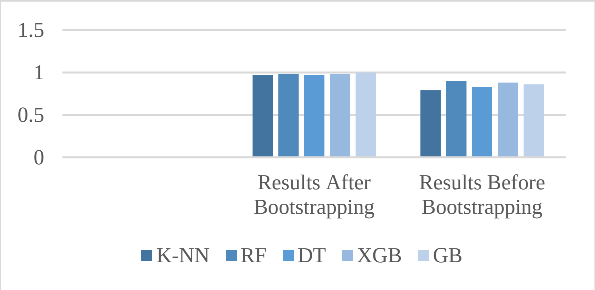
Boosting (GB) only attained lower accuracies of 0.79, 0.83, and 0.86 correspondingly. These results signify the potential improvements added by data augmentation techniques such as bootstrapping, which reduces overfitting asymmetry risks and improves the model, in addition to increasing the reliability of predictions. A general positive increase in all the models-in-general reflects how preprocessing is essential in attaining quality predictive outcome for any machine-learning task.

Table 2
Results Before and After bootstrapping

Models	Results After Bootstrapping	Results Before Bootstrapping
K-NN	0.97	0.79
RF	0.98	0.90
DT	0.97	0.83
XGB	0.98	0.88
GB	1.00	0.86

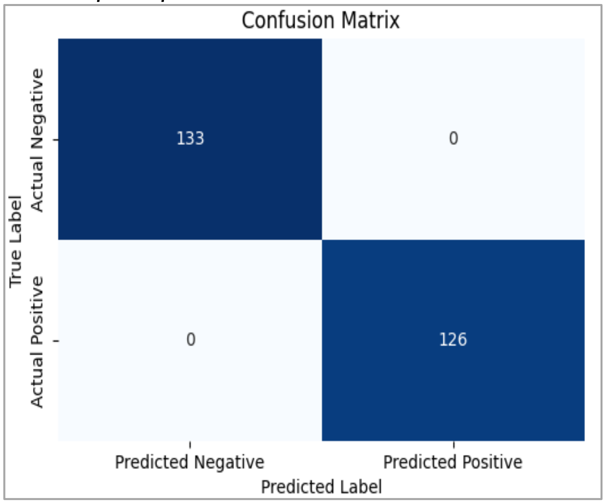
All the models have shown considerable performance improvements after bootstrapping, as presented by the marked difference in Figure 2. The merits of this data enhancement technique, which would soon be discovered by the reader, are clear and unequivocal. Gradient Boosting (GB) bagged 100% accuracy (1.00), while following in a close string were Random Forest (RF) and Xtreme Gradient Boosting (XGB) at 0.98. All three showed robustness with the enriched dataset. K-Nearest Neighbors (KNN) drew the largest relative gain by climbing from 0.79 before bootstrapping to 0.97; the same could be said of Decision Tree (DT), which had a remarkable jump up from 0.83 to 0.97. These statistics strongly endorse bootstrapping as a potential means of improving model reliability and generalization, especially in cases of datasets that are highly imbalanced.

Figure 1
Histogram-based comparisons of all models



The confusion matrix in Figure 3 shows that it has perfectly classified the model, since there are no misclassifications. It was accurately predicted negative all the 133 actual negatives, while accurate positive was given to 126 out of the 133 actual positives. Thus it very clearly indicates high precision with bulk for the performance of the model very well and indicates the reliability of the classification between the two classes. This indicates effective preprocessing steps and machine learning algorithm for the dataset in use.

Figure 2
Result of Confusion Matrix



From the findings shown in Table 3, the Gradient Boosting (GB) model performs perfectly for both "Normal" and "Abnormal" classes. The score of 1.00 for each of the classes indicates that the model has been predicted perfectly across all metrics including F1-score, precision, and recall since 1.00 is given for both the classes. In other words, the GB model predicts all true positives and true negatives; in fact, there are no false positives or false negatives. This level of success indicates that the model generalizes unusually well on test data, demonstrating robustness and effectiveness using the augmented and balanced dataset derived through SMOTE and bootstrapping.

Table 3
Result of Gradient Boost (GB).

Accuracy	Target Class	F1	Precision	Recall
1.00	Normal	1.00	1.00	1.00
	Abnormal	1.00	1.00	1.00

Comparison with Earlier Research

The proposed approach comparatively improves over the earlier research, which had an accuracy of 99%, with 100% accuracy as achieved by the

Gradient Boosting Technique as shown in Table 4. This marginal improvement indicates that the problem is effectively solved by our approach. Although the previous method performs quite well, our suggested method offers a tremendous improvement. The results are indicative of the best possible performance this method can achieve on this particular task, especially valuable in instances demanding accuracy.

Table 3

Performance comparison with earlier Research

References	Proposed Method	Accuracy (%)
[18]	RGXE Ensemble	99%
Our	Gradient Boosting	100%

CONCLUSION

This research elaborates machine learning methodologies, algorithms, and techniques for an early diagnosis of lower back pain. The objectives were achieved by applying class imbalance techniques, like SMOTE and bootstrapping, after creating an improved dataset using a 310-row, 12-column Kaggle dataset that constituted the features of spinal anomalies. To assess their performance, advanced machine learning models were applied to their dataset. The results discovered that the Gradient Boosting model surpassed all methods and previous research, attaining an extraordinary 1.00 accuracy score. Furthermore, every mode received fine-tuning to ensure maximum performance. The research makes very great strides in the development of reliable and accessible methodologies in the early detection of LBP and has a potential revolutionizing effect on healthcare practice.

REFERENCES

1. sammy123. (2016). *Lower Back Pain Symptoms Dataset*. Kaggle.com. https://www.kaggle.com/datasets/sammy123/lower-back-pain-symptoms-dataset
2. Abdollahi, M., Ashouri, S., Abedi, M., Azadeh-Fard, N., Parnianpour, M., Khalaf, K., & Rashedi, E. (2020). Using a motion sensor to categorize Nonspecific low back pain patients: A machine learning approach. *Sensors*, *20*(12), 3600. https://doi.org/10.3390/s20123600
3. Agnus Tom, A., Rajkumar, E., John, R., & Joshua George, A. (2022). Determinants of quality of life in individuals with chronic low back pain: A systematic review. *Health Psychology and Behavioral Medicine*, *10*(1), 124-144. https://doi.org/10.1080/21642850.2021.2022487
4. Ahmed, S. R., Ahmed, A. K., & Jwmaa, S. J. (2023). Analyzing the employee turnover by using decision tree algorithm. *2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, 1-4. https://doi.org/10.1109/hora58378.2023.10156709
5. Al-Haddad, L. A., Jaber, A. A., Hamzah, M. N., & Fayad, M. A. (2023). Vibration-current data fusion and gradient boosting classifier for enhanced stator fault diagnosis in three-phase permanent magnet synchronous motors. *Electrical Engineering*, *106*(3), 3253-3268. https://doi.org/10.1007/s00202-023-02148-z
6. Alsaadi, S. M., McAuley, J. H., Hush, J. M., Lo, S., Bartlett, D. J., Grunstein, R. R., & Maher, C. G. (2014). The bidirectional relationship between pain intensity and sleep disturbance/Quality in patients with low back pain. *The Clinical Journal of Pain*, *30*(9), 755-765. https://doi.org/10.1097/ajp.0000000000000055
7. An, Q., Rahman, S., Zhou, J., & Kang, J. J. (2023). A comprehensive review on machine learning in healthcare industry: Classification, restrictions, opportunities and challenges. *Sensors*, *23*(9), 4178. https://doi.org/10.3390/s23094178
8. Arslan, M., Mubeen, M., Akram, A., Abbasi, S. F., Ali, M. S., & Tariq, M. U. (2024). A deep features based approach using modified ResNet50 and gradient boosting for visual sentiments classification. *2024 IEEE 7th International Conference on Multimedia*

Information Processing and Retrieval (MIPR), *11*, 239-242. https://doi.org/10.1109/mipr62202.2024.00045

9. Benemaran, R. S. (2023). Application of extreme gradient boosting method for evaluating the properties of episodic failure of borehole breakout. *Geoenergy Science and Engineering*, *226*, 211837. https://doi.org/10.1016/j.geoen.2023.211837
10. Chen, S., Chen, M., Wu, X., Lin, S., Tao, C., Cao, H., Shao, Z., & Xiao, G. (2022). Global, regional and national burden of low back pain 1990–2019: A systematic analysis of the global burden of disease study 2019. *Journal of Orthopaedic Translation*, *32*, 49-58. https://doi.org/10.1016/j.jot.2021.07.005
11. Chowdhury, M. O., Huda, N., Alam, M. M., Hossain, S. I., Hossain, S., Islam, S., & Khatun, M. R. (2023). Work-related risk factors and the prevalence of low back pain among low-income industrial workers in Bangladesh: Results from a cross-sectional study. *Bulletin of Faculty of Physical Therapy*, *28*(1). https://doi.org/10.1186/s43161-023-00132-z
12. Dolesi, K., Steinbach, E., Velasquez, A., Whitaker, L., Baranov, M., & Atherton, L. (2024). A machine learning approach to ransomware detection using opcode features and k-nearest neighbors on Windows. https://doi.org/10.36227/techrxiv.172926410.04244699/v1
13. Esmaeili-Falak, M., & Benemaran, R. S. (2024). Ensemble extreme gradient boosting based models to predict the bearing capacity of micropile group. *Applied Ocean Research*, *151*, 104149. https://doi.org/10.1016/j.apor.2024.104149
14. Fatoye, F., Gebrye, T., Ryan, C. G., Useh, U., & Mbada, C. (2023). Global and regional estimates of clinical and economic burden of low back pain in high-income countries: A systematic review and meta-analysis. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1098100
15. Gaonkar, A. P., Kulkarni, R., Caytiles, R. D., & Iyengar, N. (2017). Classification of lower back pain disorder using multiple machine learning techniques and identifying degree of importance of each parameter. *International Journal of Advanced Science and Technology*, *105*, 11-24. https://doi.org/10.14257/ijast.2017.105.02
16. Gill, A. Y., Saeed, A., Rasool, S., Husnain, A., & Hussain, H. K. (2023). Revolutionizing healthcare: How machine learning is transforming patient diagnoses - a comprehensive review of AI's impact on medical diagnosis. *Journal of World Science*, *2*(10), 1638-1652. https://doi.org/10.58344/jws.v2i10.449
17. Grabovac, I., & Dorner, T. E. (2019). Association between low back pain and various everyday performances. *Wiener klinische Wochenschrift*, *131*(21-22), 541-549. https://doi.org/10.1007/s00508-019-01542-7
18. Haider, M., Hashmi, M. S., Raza, A., Ibrahim, M., Fitriyani, N. L., Syafrudin, M., & Lee, S. W. (2024). Novel ensemble learning algorithm for early detection of lower back pain using spinal anomalies. *Mathematics*, *12*(13), 1955. https://doi.org/10.3390/math12131955
19. Ijaz, M., Alfian, G., Syafrudin, M., & Rhee, J. (2018). Hybrid prediction model for type 2 diabetes and hypertension using DBSCAN-based outlier detection, synthetic minority over sampling technique (SMOTE), and random forest. *Applied Sciences*, *8*(8), 1325. https://doi.org/10.3390/app8081325
20. Islam, M. S., Asaduzzaman, M., & Rahman, M. M. (2019). Feature selection and classification of spinal abnormalities to detect low back pain disorder using machine learning approaches. *2019 1st International Conference on Advances in Science, Engineering and Robotics*

Technology (ICASERT), 1-4. https://doi.org/10.1109/icasert.2019.8934683
21. Javaid, M., Haleem, A., Pratap Singh, R., Suman, R., & Rab, S. (2022). Significance of machine learning in healthcare: Features, pillars and applications. *International Journal of Intelligent Networks*, *3*, 58-73. https://doi.org/10.1016/j.ijin.2022.05.002
22. Karabadji, N. E., Amara Korba, A., Assi, A., Seridi, H., Aridhi, S., & Dhifli, W. (2023). Accuracy and diversity-aware multi-objective approach for random forest construction. *Expert Systems with Applications*, *225*, 120138. https://doi.org/10.1016/j.eswa.2023.120138
23. Kasula, B. Y. (2021). Machine Learning in Healthcare: Revolutionizing Disease Diagnosis and Treatment. *International Journal of Creative Research in Computer Technology and Design*, *3*(3). https://jrctd.in/index.php/IJRCTD/article/view/27
24. Lamichhane, B., Jayasekera, D., Jakes, R., Glasser, M. F., Zhang, J., Yang, C., Grimes, D., Frank, T. L., Ray, W. Z., Leuthardt, E. C., & Hawasli, A. H. (2021). Multi-modal biomarkers of low back pain: A machine learning approach. *NeuroImage: Clinical*, *29*, 102530. https://doi.org/10.1016/j.nicl.2020.102530
25. Mathew, J., Singh, S. B., Garis, S., & Diwan, A. D. (2013). Backing up the stories: The psychological and social costs of chronic low-back pain. *The International Journal of Spine Surgery*, *7*(1), e29-e38. https://doi.org/10.1016/j.ijsp.2013.02.001
26. Naseer, A., & Jalal, A. (2023). Pixels to precision: Features fusion and random forests over labelled-based segmentation. *2023 20th International Bhurban Conference on Applied Sciences and Technology (IBCAST)*, *19*, 1-6. https://doi.org/10.1109/ibcast59916.2023.10712869
27. Nijeweme-d'Hollosy, W. O., Van Velsen, L., Poel, M., Groothuis-Oudshoorn, C. G., Soer, R., & Hermens, H. (2018). Evaluation of three machine learning models for self-referral decision support on low back pain in primary care. *International Journal of Medical Informatics*, *110*, 31-41. https://doi.org/10.1016/j.ijmedinf.2017.11.010
28. Organization, W. H. (2018). https://www.who.int/news-room/fact-sheets/detail/influenza-(seasonal)
29. Pinto, E. M., Neves, J. R., Laranjeira, M., & Reis, J. (2023). The importance of inflammatory biomarkers in non-specific acute and chronic low back pain: A systematic review. *European Spine Journal*, *32*(9), 3230-3244. https://doi.org/10.1007/s00586-023-07717-1
30. Rubinger, L., Gazendam, A., Ekhtiari, S., & Bhandari, M. (2023). Machine learning and artificial intelligence in research and healthcare. *Injury*, *54*, S69-S73. https://doi.org/10.1016/j.injury.2022.01.046
31. Sarker, M. (2024). Revolutionizing healthcare: The role of machine learning in the health sector. *Journal of Artificial Intelligence General science (JAIGS) ISSN:3006-4023*, *2*(1), 36-61. https://doi.org/10.60087/jaigs.v2i1.96
32. Shim, J., Ryu, K., Cho, E., Ahn, J. H., Kim, H. K., Lee, Y., & Lee, S. H. (2021). Machine learning approaches to predict chronic lower back pain in people aged over 50 years. *Medicina*, *57*(11), 1230. https://doi.org/10.3390/medicina57111230
33. Singh, D., Singla, J., Rahmani, M. K., Ahmad, S., Rehman, M. U., Jha, S., Prashar, D., & Nazeer, J. (2023). Lumbar spine disease detection: Enhanced CNN model with improved classification accuracy. *IEEE Access*, *11*, 141889-141901. https://doi.org/10.1109/access.2023.3342064
34. Stefane, T., Santos, A. M. dos, Marinovic, A., & Hortense, P. (2013). Dor lombar crônica: intensidade de dor, incapacidade e

qualidade de vida. *Acta Paulista de Enfermagem*, *26*(1), 14–20. https://doi.org/10.1590/s0103-21002013000100004

35. Sun, Z., Wang, G., Li, P., Wang, H., Zhang, M., & Liang, X. (2024). An improved random forest based on the classification accuracy and correlation measurement of decision trees. *Expert Systems with Applications*, *237*, 121549. https://doi.org/10.1016/j.eswa.2023.121549

36. Tang, Y., Chang, Y., & Li, K. (2023). Applications of k-nearest neighbor algorithm in intelligent diagnosis of wind turbine blades damage. *Renewable Energy*, *212*, 855-864. https://doi.org/10.1016/j.renene.2023.05.087

37. Wang, Y., Verba, V., Bezumnov, D., & Tarasenko, E. (2019). Neural network using for prediction spinal diseases. In *Conference of Open Innovations Association*, *FRUCT* (No. 24, pp. 790-796). FRUCT Oy. https://fruct.org/publications/volume-24/acm24/files/Wan.pdf

38. Yagin, F., Alkhateeb, A., Raza, A., Samee, N., Mahmoud, N., Colak, C., & Yagin, B. (2023). An explainable artificial intelligence model proposed for the prediction of myalgic encephalomyelitis/Chronic fatigue syndrome and the identification of distinctive metabolites. *Diagnostics*, *13*(23), 3495. https://doi.org/10.3390/diagnostics13233495