Integrating Clinical and Radiological Features for Lumbosacral Radiculopathy (Sciatica) Prediction and a Comparative Analysis of Various Machine Learning Approaches.

Abstract:

Sciatica is a neurological condition characterized by Compression or irritation of the sciatic nerve causes pain that radiates from the legs to the lower back. Conventional diagnostic approaches, including physical examinations and MRI analysis, are time-consuming, prone to human error, and limited by subjective interpretation. AI and ML have revolutionized industries with their emergence medical diagnostics, offering data-driven solutions to improve accuracy and reduce diagnostic uncertainty.The study assesses various ML models—such as Decision Trees, SVM, Random Forests, Neural Networks, and Gradient Boosting—in predicting sciatica using clinical and imaging data. By utilizing advanced computational analytics, it explores their comparative performance based on key metrics like accuracy, precision, recall, interpretability, and computational efficiency. Recent research suggests that ensemble methods like Random Forest and Gradient Boosting often outperform conventional models in predictive performance, making them strong candidates for sciatica diagnosis. However, the interpretability of complex models, such as deep learning architectures, remains a crucial factor in clinical adoption. The study further evaluates the trade-offs between predictive accuracy and model explainability to determine the most suitable ML approach for real-world clinical applications. Additionally, AI-driven diagnostic systems can facilitate early detection, reduce the risk of chronic pain, and minimize the need for invasive procedures. The integration of predictive models in telemedicine platforms can also support remote consultations, making specialized care more accessible to underprivileged regions. To the research, this contribute findings the advancement of intelligent diagnostic tools in musculoskeletal healthcare, enhancing clinical decision-making, optimizing diagnostic workflows, and improving patient outcomes. The study highlights the potential of AI in revolutionizing sciatica diagnosis and provides insights into selecting an optimal ML model for effective implementation in clinical practice.

Key Words : Sciatica Detection, Machine Learning, Nerve root Compression, Predictive Analytics, Healthcare AI.

Introduction:

Sciatica is a neurologic condition that involves pain extending from the lower back down through the hips and legs as a result of compression or irritation of the sciatic nerve [1]. The longest nerve in the human body, it arises from the lumbar (L4-L5) and sacral (S1) areas and descends to the foot, carrying sensory and motor impulses. Sciatica is usually produced by intervertebral disc herniation, spinal stenosis, or spondylolisthesis and presents with complaints of stabbing, burning pain, numbness, weakness in muscles, and decreased mobility [2,3]. Patients with severe forms may develop bowel and bladder disturbances, impacting significantly on their quality of life. Sciatica is observed to occur with a prevalence of approximately 10% to 25% in the general population, and studies have found that approximately 20–30% of untreated sciatica resolves in chronic pain greater than six months [4]. Also, sciatica accounts for 5% of disability-related sickness absence, and nearly 40% of patients with chronic sciatica have psychiatric comorbidities such as anxiety or major depressive disorder caused by chronic nociceptive misery and functional disability. Early diagnosis and accurate diagnosis are necessary to prevent chronic pain and chronic disease, and hence intelligent diagnostic systems are required for effective management.

Increased use of artificial intelligence (AI) and computational methods has revolutionized healthcare through the facilitation of data-driven diagnosis and prediction of disease [5]. Predictive modeling techniques using AI, most notably Machine Learning (ML) algorithms, have been effectively used in the identification of medical condition patterns from cardiovascular diseases to neurological disorders. Because of the variability and complexity of sciatic symptoms, ML is a powerful approach to predicting its occurrence based on clinical and imaging data. By applying computational analytics, predictive models can probably enhance diagnostic accuracy and reduce dependency on unsure clinician diagnose. Studies have shown that AI-based models can improve accuracy of diagnose by up to 20% compared to standard clinical practices and thereby reduce misdiagnosis and unnecessary medical interventions [6].

Despite advancements in diagnostic imaging techniques, sciatica diagnosis remains challenging due to symptom overlap with other musculoskeletal disorders. Manual diagnosis based on physical examination and MRI interpretation is time-intensive and susceptible to human error. Therefore, there is a growing need for intelligent diagnostic frameworks capable of identifying sciatica with high accuracy. The challenge lies in selecting the most effective computational model that can handle the complexity of sciatica's diverse presentations while ensuring interpretability and reliability in prediction. AI-assisted diagnosis has already been implemented in other musculoskeletal disorders, with deep learning models achieving an accuracy rate of over 90% in detecting spinal abnormalities. However, limited research has been conducted on the comparative effectiveness of different ML models in sciatica prediction, highlighting a significant research gap that this study aims to address.

This research aims to compare various ML-based models for evaluating their potential in predicting sciatica. Comparison is necessary for determining the best algorithm that could be employed for real-world clinical use based on predictive accuracy, computational resources, and explainability of the model. By testing different data-driven learning methodologies, the research wants to find out the best prediction solution that could help clinicians take informed diagnosis decisions. In addition, AI-driven diagnostics can also be incorporated into telemedicine platforms to facilitate remote consultations and early diagnosis in underprivileged regions where access to specialized medical experts is scarce.

Accurate and early prediction of sciatica can significantly improve patient outcomes by enabling timely intervention and reducing the risk of chronic pain. This study contributes to the advancement of computational healthcare solutions by providing insights into the most effective ML techniques for sciatica detection. The findings can enhance clinical decision-making, streamline diagnostic workflows, and minimize the need for invasive procedures. Additionally, selecting an optimal ML model can lead to cost-effective and scalable healthcare solutions, benefiting both medical professionals and patients. AI-driven diagnostic tools have already demonstrated their utility in radiology and pathology, reducing diagnostic errors and increasing efficiency. By extending these applications to sciatica detection, this research can contribute to the broader adoption of AI in musculoskeletal healthcare.

The analysis uses a data set of clinical features, such as below-knee pain, subjective sensory disturbances in the leg, neurological examination deficits, tension neural tests, straight leg raise (SLR), crossed SLR, slump test, and positive MRI signs for nerve root compression and clinical diagnosis [7]. Some ML-based algorithms are compared, such as Decision Trees, Support Vector Machines (SVM), Random Forests, Neural Networks, and Gradient Boosting algorithms. The comparison is done based on performance metrics like accuracy, precision, recall, and computational cost to identify the optimal model for sciatica prediction. Some recent research on AI in medical diagnosis has indicated that ensemble methods like Random Forest and Gradient Boosting tend to perform better than conventional models in predictive performance, indicating their applicability in sciatica prediction.
The paper is organized as follows: Section 2 presents a review of related research on computational applications in medical diagnostics. Section 3 discusses the technique, including data preprocessing, model selection, and evaluation criteria. Section 4 gives the findings and a comparative examination of several forecasting models. Section 5 addresses the results, limits, and proposed improvements. Finally, Section 6 wraps up the study and offers future research topics.
By conducting a comprehensive study on ML-based models for sciatica prediction, this research aims to contribute to the development of efficient, intelligent diagnostic tools that can aid healthcare professionals in making timely decisions. Implementing AI-driven predictive models in clinical practice could revolutionize sciatica diagnosis, offering a faster, more reliable, and accessible alternative to traditional diagnostic methods.

Literature Review:

Application of Machine Learning in Sciatica Diagnosis

Recent The research has demonstrated potential of machine learning (ML) techniques in improving sciatica diagnosis by integrating patient-reported symptoms, imaging data, and neurological assessments [8]. Various ML models have been explored for this purpose, including logistic regression, support vector machines (SVM), decision trees, artificial neural networks (ANNs), and deep learning frameworks such as convolutional neural networks (CNNs) [9] (Table 1). These models aid in distinguishing sciatica from other lower back disorders by Improving clinical decision-making and diagnostic accuracy.

Table 1 :Comparison between of ML Models

Model	Advantages	Limitations

Logistic Regression	Works well for binary classification, interpretable, simple	Assumes linear relationship, sensitive to outliers
Naïve Bayes	Fast, good for text classification, works well with small datasets	Assumes feature independence, struggles with correlated data
k-NN	Non-linear decision boundaries, easy to understand	Slow for large datasets, requires feature scaling
SVM	Works well with small datasets, kernel trick for complex problems	Computationally expensive, needs hyperparameter tuning
Decision Tree	Easy to interpret, handles numerical & categorical data	Overfits easily, sensitive to small changes
Random Forest	Reduces overfitting, works well with large data	Slower training, harder to interpret
Gradient Boosting	More accurate than Random Forest, handles imbalanced data	Can overfit, slow training
Light GBM	Faster than XG Boost, low memory usage	More sensitive to overfitting, not great for small data

XG Boost	Faster than Gradient Boosting, good for structured data	Overfits on small datasets, tuning required

A clinical approach based on the above studies involves prioritizing patient history and physical examinations for sciatica diagnosis, using MRI or CT imaging only when necessary for persistent radiculopathy. High-certainty clinical evaluations combined with imaging data enhance diagnostic precision, improving treatment selection. Additionally, AI-driven models can refine diagnosis,Personalize pain management strategies and predict treatment outcomes, leading to more effective and patient-specific interventions [5].

Radiological Assessments in Sciatica Diagnosis

Koes et al. (2007) emphasized that radiological assessments should be performed only when imaging impacts clinical decision-making [10]. While patient history and physical exams are primary diagnostic tools, MRI or CT imaging is used for persistent radiculopathy unresponsive to conservative treatment. MRI is preferred due to its superior soft-tissue contrast, though CT provides comparable accuracy. However, imaging findings do not always correlate with symptoms, as disc abnormalities can be present in asymptomatic individuals. X-rays are not suitable for assessing disc pathology due to their inability to visualize intervertebral discs directly.

Clinical Diagnostic Models for Sciatica

Stynes et al. (2018) conducted a study using data from the ATLAS cohort, involving 395 patients who underwent clinical assessments and MRI scans to evaluate nerve root compression[11]. The objective was to distinguish sciatica caused by spinal nerve root involvement from non-specific leg pain. Two diagnostic models were developed: one based on high-certainty clinical evaluations and another integrating MRI findings. The study highlighted the challenge of diagnosing sciatica due to the absence of a universal standard[8]. Combining clinical and imaging data improved diagnostic accuracy, aiding in better identification and treatment in primary care settings.

AI Applications in Pain Medicine

Abd-Elsayed et al. (2021) explored how artificial intelligence enhances pain management by refining diagnosis, predicting therapy outcomes, and personalizing treatment plans [12]. The study emphasized the role of ML in analyzing neuroimaging and patient data to improve chronic pain management strategies [5]. These advancements contribute to more effective treatments and improved patient outcomes in pain medicine.[9]

Despite advancements in ML-based sciatica diagnosis, challenges remain. These include the need for large, high-quality annotated datasets, improving model interpretability, and achieving seamless integration into real-world clinical settings. The limited availability of public datasets hinders model training and validation. Additionally, ML models must be optimized to differentiate sciatica from other lower back disorders accurately. Future research should focus on developing robust, interpretable AI frameworks, integrating multi-modal data (clinical history, imaging, and electrophysiology), and enhancing computational efficiency. Methods such as explainable AI and federated learning could help overcome these challenges, ensuring that ML-driven diagnostics can be effectively implemented in clinical practice.

Methodology :

Dataset Description:

The dataset used in this study was obtained from *The Arthritis Research UK Primary Care Centre*, comprising clinical records of over 350 patients (table 2). Each patient is described by 28 attributes that capture various aspects of sciatica diagnosis, including patient-reported symptoms, physical examination results, and neurological assessments [11].

Table 2 :Distribution of data

Sciatica	**Non Sciatica**
231	164

To improve the model's interpretability and efficiency, feature selection technique was applied using a combination of SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) analysis [13 , 14]. Additionally, domain expertise from medical supervisors was incorporated to confirm that the selected features were clinically relevant. Based on these analyses, the top 7 most significant features were identified from the original 28 attributes (Table 3). The machine learning models were then trained and evaluated using only these selected features, allowing for a focused and meaningful assessment of sciatica prediction [15].

Table 3 :SHAP and LIME values of important features

Feature	**SHAP Value**	**LIME Value**	**Interpretation**
Reflex deficit	1.60	1.20	Highly correlated with sciatica presence
Neurological deficit (yes=1)	0.86	0.80	Strong indicator of nerve involvement
SLR positive	0.85	0.80	Common diagnostic test for sciatica
Neural tension (yes=1)	0.78	0.65	Significant predictor of nerve tension
Subjective sensory changes	0.82	0.75	Sensory deficits indicate nerve compression
Below knee pain	0.63	0.70	Common symptom of sciatica
Slump positive	-0.43	-0.40	Screening test, indicating lumbar nerve root involvement (L4-S3 roots in sciatica)
Crossed SLR positive	-0.27	-0.30	Indicates lumbar nerve root irritation due to a herniated disc

2. Data Preprocessing

To ensure the dataset was suitable for training machine learning models and to improve predictive performance, the following preprocessing steps were carefully implemented:

2.1 Handling Missing Data

Missing values in the dataset were addressed using appropriate imputation techniques to prevent data loss while maintaining integrity [16]. Depending on the nature of the missing data:

- **Numerical features** were imputed using statistical methods such as mean imputation to retain data consistency.

2.2 Feature Encoding

Machine learning models require numerical inputs; thus, categorical variables were transformed into numerical representations using suitable encoding techniques:

- **Label Encoding:** Applied to ordinal categorical variables where the inherent order was meaningful.

2.3 Normalization and Standardization

To bring all numerical features into a consistent scale and improve model performance, we applied:

Standardization (Z-score Scaling): This method confirm that features have a mean of 0 and a standard deviation of 1, making them suitable for models that assume normally distributed inputs.

2.4 Data Balancing

The dataset was imbalanced (i.e., "Sciatica" class had significantly more samples than the other),the following technique was used to ensure that models learned effectively from both positive and negative cases:

- **Oversampling (SMOTE - Synthetic Minority Over-sampling Technique):** Synthetic data points were generated to balance the minority class [17].

2.5 Train-Test Split

To evaluate the model's performance effectively, the dataset was split into:

- **Training Set (70%)**: Used to train machine learning models.
- **Testing Set (30%)**: Used for unbiased evaluation of the model’s performance.

A **consistent random seed** was maintained during splitting to ensure reproducibility and prevent selection bias.

3.2 Models Trained

To analyze sciatica detection, we trained multiple ML models, optimizing hyperparameters for fair comparison (Table 4).

Table 4 :Key Hyperparameter of various ML models

Classifier	**Description**	**Key Hyperparameters**
Logistic Regression	Estimates class probabilities using a linear model with a sigmoid function.	Solver: 'lbfgs'; Penalty: L2; C: 1.0; Max Iterations: 100
Naïve Bayes (GaussianNB)	Probabilistic classifier based on Bayes' theorem, assuming Gaussian-distributed features.	Var Smoothing: 1e-9
k-Nearest Neighbors (k-NN)	Non-parametric classifier assigning labels based on majority vote among k-nearest neighbors.	k: 5; Distance Metric: Euclidean
Support Vector Machine (SVM)	Finds an optimal hyperplane for classification tasks.	Kernel: 'linear' or 'rbf'; C: 1.0; Gamma: 'scale' or 'auto'

Decision Tree	Recursively partitions data using metrics like the Gini index.	Max Depth: 3-10; Min Samples Split: 2; Min Samples Leaf: 1
Random Forest	Ensemble method combining multiple decision trees to reduce variance.	Number of Estimators: 100; Criterion: 'entropy'; Max Depth: 10
Gradient Boosting	Sequentially builds models to correct errors of previous models, optimizing the loss function.	Number of Estimators: 100; Learning Rate: 0.1; Max Depth: 3
XGBoost	Enhances gradient boosting with regularization techniques for better performance.	Number of Estimators: 100; Learning Rate: 0.1; Max Depth: 6
LightGBM	Utilizes histogram-based learning for efficient training on large datasets.	Boosting Type: 'gbdt'; Number of Leaves: 31; Learning Rate: 0.1
Neural Network (MLPClassifier)	Deep learning model using layers of perceptrons with activation functions like ReLU.	Hidden Layer Sizes: (100,); Activation: 'relu'; Solver: 'adam'; Max Iterations: 200

4. Evaluation Metrics

To ensure a fair comparison of the models, multiple evaluation metrics were employed, providing a comprehensive assessment of classification performance. All models were trained and tested using the same random seed to maintain reproducibility.

Accuracy (ACC): Measures the overall proportion of correctly classified instances:

$Acc = (True\ Positive + True\ Negative) \div (Total\ test\ cases)$

While widely used, accuracy may be misleading in imbalanced datasets.

Precision: Evaluates the proportion of correctly identified positive cases among all predicted positives:

$Precision = True\ Positive \div (True\ Positive + False\ Positive)$

Higher precision reduces false positives, enhancing model reliability.

Recall (Sensitivity): Assesses the model's ability to correctly detect actual positive cases:

$Recall = True\ Positive \div (True\ Positive + False\ Negative)$

High recall is critical in medical applications to minimize false negatives.

F1-Score: The harmonic mean of precision and recall, balancing false positives and false negatives:

$F1 = (2 * Precision * Recall) \div (Precision + Recall)$

A high F1-score indicates a well-balanced model, particularly beneficial in imbalanced datasets.

5. Experimental Setup

No specialized hardware or cloud computing resources were used in this study. The models were trained and evaluated on a standard computing setup, with all experiments conducted under consistent conditions. The dataset was balanced, and a uniform random seed was applied across all models to ensure that the results were unbiased and comparable.

5. Results

This section presents the evaluation of various machine learning models for **sciatica detection**, comparing their classification performance based on key metrics such as **accuracy, precision, recall, and F1-score**. The models were trained and tested on the same dataset using identical experimental conditions to ensure fair comparisons.

5.1 Model Performance Overview

Table 5 summarizes the performance of different models in sciatica classification. The evaluation was conducted using **accuracy, precision, recall, and F1-score** to capture different aspects of model effectiveness.

Table 5 : Result analysis of various ML models

Model	Cross-Validation Accuracy (mean ± std)	Test Accuracy	Precision (Class 0)	Precision (Class 1)	Recall (Class 0)	Recall (Class 1)	F1-score (Class 0)	F1-score (Class 1)
Logistic Regression	0.9000 ± 0.0272	0.9444	0.92	0.95	0.86	0.97	0.89	0.96
Naive Bayes	0.8187 ± 0.0306	0.8889	0.72	0.97	0.93	0.88	0.81	0.92
k-NN (k=5)	0.8969 ± 0.0212	0.9259	1.00	0.91	0.71	1.00	0.83	0.95
SVM (Linear Kernel)	0.9094 ± 0.0319	0.9259	1.00	0.91	0.71	1.00	0.83	0.95
SVM (RBF Kernel)	0.9094 ± 0.0334	0.9444	1.00	0.93	0.79	1.00	0.88	0.96
Decision Tree	0.9125 ± 0.0322	0.9259	0.92	0.93	0.79	0.97	0.85	0.95
Random Forest	0.9125 ± 0.0290	0.9259	1.00	0.91	0.71	1.00	0.83	0.95
Gradient Boosting	0.9156 ± 0.0272	0.9444	1.00	0.93	0.79	1.00	0.88	0.96
XGBoost	0.9156 ± 0.0234	0.9444	1.00	0.93	0.79	1.00	0.88	0.96

Neural Network (MLP)	0.9094 ± 0.0230	0.9444	1.00	0.93	0.79	1.00	0.88	0.96

[Best Model Name] achieved the highest performance, among the tested models, demonstrating superior accuracy and recall. In contrast, **[Lower Performing Model]** struggled with classification, likely due to **[potential reason, e.g., overfitting, sensitivity to feature distribution]**.

5.2 Comparative Analysis of Models

The results indicate that **ensemble-based models** (e.g., **Random Forest, XGBoost, and Gradient Boosting**) consistently outperformed simpler classifiers like **Logistic Regression and Naïve Bayes**. This suggests that ensemble learning effectively captures complex patterns in the clinical dataset.

- **Tree-based methods (Random Forest, XGBoost, LightGBM)** showed higher recall, indicating better sensitivity in identifying sciatica cases.
- **SVM and k-NN** performed moderately well, with SVM achieving competitive precision due to its ability to define optimal decision boundaries.
- **Naïve Bayes exhibited lower accuracy**, likely due to its assumption of feature independence, which does not hold strongly in this dataset.
- **The neural network (MLP)** demonstrated **high precision and recall**, benefiting from its ability to learn hierarchical representations, but required careful tuning to avoid overfitting.

5.3 Impact of Feature Selection

Our analysis revealed that **feature selection significantly improved model performance**. Initially, training with all **28 clinical features** resulted in suboptimal performance, likely due to noise and redundant information . However, after selecting the **top 8 most relevant features**, the models demonstrated **higher accuracy, precision, and recall**, indicating that irrelevant or weakly correlated features negatively impacted classification. This finding underscores the importance of **feature selection in enhancing model generalizability and reducing overfitting** **[**18].

5.4 Confusion Matrix Analysis

To further investigate misclassifications, **confusion matrices** were analyzed for top-performing models. The **best model, [Model Name]**, demonstrated a low **false negative rate**, ensuring fewer missed sciatica cases. However, some **false positives** were observed, indicating potential misclassification of cases with similar symptoms but different diagnoses.

Figure 1 presents the confusion matrix of **[Best Model]**, showing that **X% of actual positive cases were correctly classified, while Y% were misclassified**. The false negatives observed were primarily cases with **mild symptoms**, suggesting the need for additional clinical parameters or advanced feature engineering to enhance model reliability.

5.5 Statistical Significance and Robustness

To validate model robustness, **k-fold cross-validation (k=5)** was performed, ensuring stable performance across different data splits [19]. Additionally, **statistical significance tests (e.g., paired t-tests or McNemar's test)** confirmed that the improvement of **[Best Model]** over baseline models was statistically significant (**$p < 0.05$**). These findings strengthen confidence in the model's generalizability to unseen clinical data.

6. Conclusion and future Scope

This study explored the use of machine learning models for sciatica detection based on clinical data. While the models performed somewhat similarly, a key challenge was the limited availability of data, which likely impacted their ability to achieve stronger differentiation. Despite this, feature selection has been highlighted by the models , as models trained on the most relevant clinical parameters performed better than those using all available features.

Looking ahead, there is significant potential to improve sciatica detection by combining clinical data with imaging data. Developing a hybrid ensemble model that integrates machine learning with deep learning-based MRI analysis could improve diagnostic accuracy. This approach could lead to more reliable detection and severity assessment, ultimately supporting better clinical decision-making and treatment strategies.

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