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Comparative Analysis of Selected Machine Learning Algorithms for Lumbar Spinal Stenosis Classification.

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Abstract

Lumbar spinal stenosis (LSS) represents a prevalent etiology of low back discomfort among the adult population, attributable to a constriction that exerts pressure on the spinal cord or nerve roots. Accurate and timely diagnosis is crucial for effective management and treatment of LSS. This study presented a Machine learning and deep learning framework designed to classify lumbar spinal stenosis (LSS) severity by leveraging imaging data. The dataset of MRI images was obtained from the Kaggle online repository, the data came in a CSV file with a DCOM image folder. The dataset contained 48,692 images. The CSV and DCOM images were linked together. In doing this, missing, null, and invalid data were sought in the dataset and removed. Outliers too were checked and sorted out. 80% were used for training and 20% were used for testing. Using machine learning algorithms like Support Vector Machines (SVM) and Custom-made CNN. The models were trained to classify varying degrees of LSS severity, ranging from mild to severe. The models were evaluated using performance metrics such as accuracy, precision, recall, and F1-scores to quantify the model's effectiveness. Due to the class imbalance in the dataset, the SVM and Custom-CNN models perform exceptionally well in the "mild" class but struggle with "severe" and "moderate" classes The results demonstrated that support vector machine (SVM), and Custom-made CNN models achieved accuracies of 89% and 90% respectively in classifying LSS severity. This study shows that the Custom-made CNN model performs better in classification of Lumbar spinal stenosis than the traditional Machine learning model using MRI imaging datasets. Cross-validation should be implemented to ensure the performance of the model is consistent across other subsets of data.

Keywords: Machine Learning, Deep Learning, Lumbar Spinal Stenosis (LSS), Support Vector_Machine (SVM), Convolutional Neural Networks (CNN) Classification Models, Medical Imaging Resonance.

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1. Introduction

Lumbar spinal stenosis (LSS) represents a prevalent etiology of low back discomfort among the adult population, attributable to a constriction that exerts pressure on the spinal cord or nerve roots. Various pathological conditions contribute to the development of LSS, encompassing disc herniation, spondylolisthesis, neoplasms, fractures, and other degenerative alterations. The phenomenon of back pain is frequently encountered in clinical practice (Lafian and Torralba, 2018). The prevalence of this pathological condition is escalating, particularly within the geriatric demographic, which is increasingly susceptible to obesity and a sedentary lifestyle (Suo et al., 2023). Lumbar spinal stenosis (LSS) is a widespread and debilitating disorder among the elderly, impacting an estimated 103 million individuals globally (Katz et al., 2022). In recent decades, advanced degenerative LSS has emerged as the primary indication for spinal surgical intervention among individuals aged 65 years and older (Deer et al., 2019). The diagnostic process for LSS is intricate, primarily due to the complexities associated with interpreting imaging findings and the restricted availability of sophisticated diagnostic modalities. While MRI and CT imaging are recognized for their efficacy, they often present significant financial burdens and may not always be readily accessible (Rangwalla et al., 2024). For instance, there exists a multitude of classification systems designed to assess the severity of stenosis, which may be categorized as 'mild,' 'moderate,' or 'severe,' among other potential designations (Tumko et al., 2024). In recent years, advancements in medical technology have revolutionized treatment approaches, leading to groundbreaking innovations (Zhou et al., 2024). Machine learning (ML) models, including deep convolutional neural networks (CNN), have already been successfully applied for evaluation of LSS and other degenerative changes with high accuracy in various approaches (Lehnen et al., 2021)

2. Related Work

Traditional methods of image interpretation can be time-consuming and subject to human error. However, AI can process and analyze images at a much faster rate, significantly reducing the time it takes to diagnose a patient. (Khalifa and Albadawy 2024). Imaging is still used to evaluate patients with spinal disorders, and its utility has contributed to a rise in the use of popular spinal imaging modalities (Harkey et al., 2018). Kim et al., (2020) investigated with random forest classifier aimed at predicting surgical outcomes for patients diagnosed with lumbar spinal stenosis (LSS), employing preoperative clinical data in their analysis. Their findings indicated that various types of data, including demographic information, comorbid conditions, and clinical evaluations, could be instrumental in forecasting therapeutic outcomes. Cheng et al., (2021) employed conventional machine learning techniques, such as support vector machines (SVM) and decision trees, to evaluate the severity of LSS by leveraging a comprehensive set of clinical, social, and imaging data.

The findings from this study indicated that the accuracy levels achieved via these algorithms substantially exceeded those of traditional methodologies, thereby enhancing diagnostic proficiency. Hallinan et al., (2021) presented a comprehensive deep-learning framework for the automated detection and classification of central canal, lateral recess, and neural foraminal stenosis utilizing both axial and sagittal MRI sequences. The model exhibited a high degree of accuracy and was found to be comparable to radiologists in the identification of central canal and lateral recess stenosis, although it demonstrated slightly diminished concordance for neural foraminal stenosis. Liu et al., (2021) elucidated that machine learning algorithms possess the capability to furnish substantial metrics for the assessment of spinal deformities' severity, thereby indicating that analogous methodologies may prove beneficial in evaluating the severity of lumbar spinal stenosis. This research underscores the potential of machine learning (ML) models in amplifying the efficacy of clinical practice. Won et al., (2020) assessed the efficacy of the computer-assisted spinal stenosis classification system by evaluating the concordance between experts proficient in CNN classifications and a diagnostic concordance between two independent experts. For the detection phase, they employed the Faster R-CNN model, and for the classification phase, they utilized the VGG network. Upon completion of the grading concordance, the discrepancies in outcomes between each expert and the trained models were minimal, with the final concordance between the trained model and the expert reaching 74.9% and 77.9%, respectively. Lakshminarayanan and Yuvaraj (2020) introduced a methodology for the analysis and classification of spinal vertebrae images, the images were scrutinized and classified into distinct disc categories employing the CNNConvNet algorithm. They demonstrated that the CNN system outperformed the Support Vector Machine (SVM) system. However, the precision of the SVM was recorded at 90%, whereas the CNN achieved a precision of 96.9%. Lu et al., (2018) categorize MRI lumbar spinal stenosis utilizing Convolutional Neural Networks (CNN), employing natural language processing to derive labels corresponding to various types and severities of spinal stenosis from radiological diagnoses. The researchers implemented the U-net architecture for the segmentation of lumbar spine vertebrae and the precise localization of the intervertebral disc levels. In the vertebral body segmentation task, the standards ensured that the algorithm could effectively exclude all lumbar intervertebral discs. The pass rate for the test cohort, following these parameters, was 94%.

3. Methodology

This section describes the dataset and the model for classifying lumbar spinal stenosis.

3.1 Dataset and Preprocessing

The dataset of Lumbar MRI images was obtained from the Kaggle online repository, the dataset came in a CSV file and a DCOM image folder in sagittal and axial form. The CSV was linked with 48,692 DCOM images. Consequently, we transformed the DCOM images into a JPG format to enhance their manageability and the processing of images. Data cleaning was carried out to get rid of incorrect and incomplete data. In doing this, missing, null, and invalid data were sought in the dataset and removed. Outliers too were checked and sorted out. Image Data Generator was employed for data augmentation. The following augmentations were implemented:

Rescaling: The pixel values are normalized to the interval [0, 1].

Rotation: Images were subjected to random rotation of up to 20 degrees. Width and height shifts: The images were randomly shifted both horizontally and vertically.

Shear: Shear transformations were applied. Zoom: Random zooming in or out is performed.
Horizontal flip: Images are randomly flipped in the horizontal direction.

3.2. Loading Data

The dataset was splited using 80% for training and 20% for testing Model Training and Testing

Two machine learning models, Support Vector Machine (SVM) and Custom-made CNN model, were employed for the classification task. The steps include:

3.2.1. Model Training: Both SVM and Custom-made CNN models were trained on the training set.

3.2.2. Model Testing: The trained models were then tested on the testing set to evaluate their performance.

Evaluation Metrics: The performance of the models was assessed using a variety of evaluation metrics, including Accuracy: Measures the overall correctness of the model by comparing the predicted values to the actual values. Precision: Indicates the proportion of true positive predictions among all positive predictions, highlighting the model's accuracy in identifying positive cases. Recall: Reflects the model's ability to correctly identify all relevant instances (true positives). F1-Score: A harmonic mean of precision and recall, providing a single metric that balances both concerns.

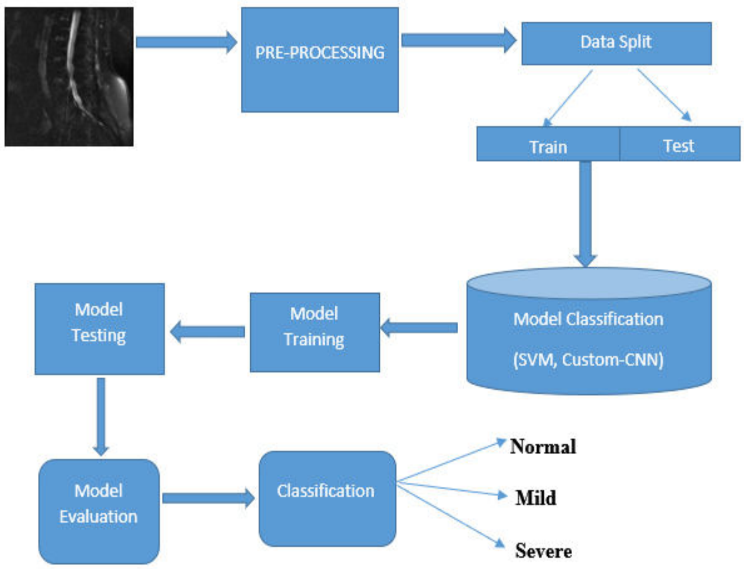


Figure 1: Classification Model for Lumbar Spinal Stenosis using SVM and CNN

4. Results.

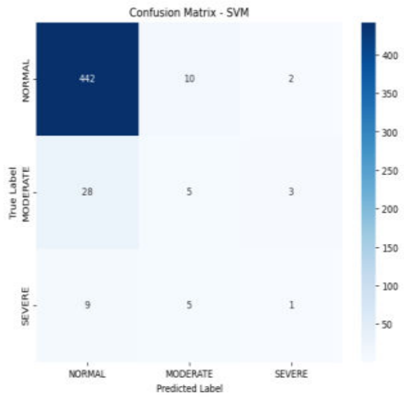
The code was built in Python environment using libraries like OpenCV, numpy, tensorflow, scikit-learn, matplotlib and seaborn. Using Windows OS corei7 8th Gen and Jupyter Notebook IDE.

Classification report for SVM

Accuracy: 0.8871287128712871

Classification Report:

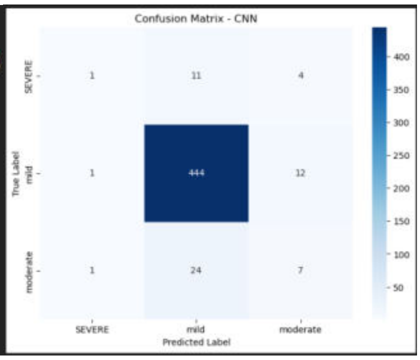
	precision	recall	f1-score	support
mild	0.92	0.97	0.95	454
moderate	0.25	0.14	0.18	36
severe	0.17	0.07	0.10	15
accuracy			0.89	505
macro avg	0.45	0.39	0.41	505
weighted avg	0.85	0.89	0.87	505

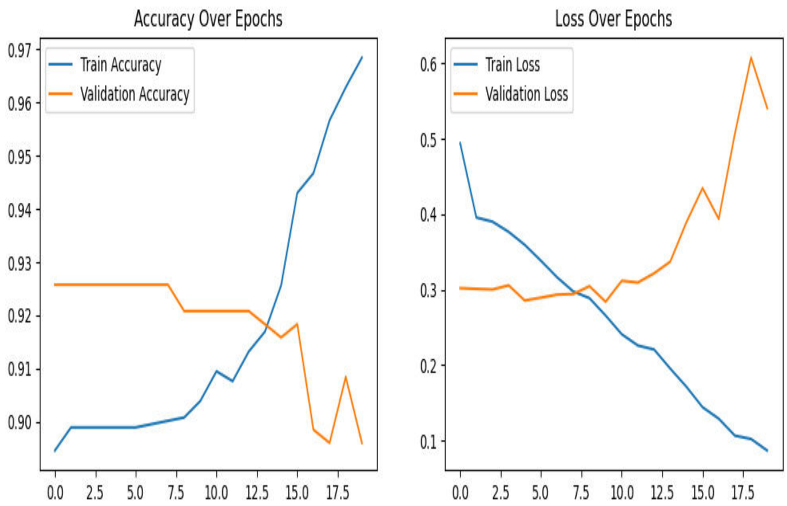


Classification report for Custom-made CNN

Classification Report:

	precision	recall	f1-score	support
SEVERE	0.33	0.06	0.11	16
mild	0.93	0.97	0.95	457
moderate	0.30	0.22	0.25	32
accuracy			0.90	505
macro avg	0.52	0.42	0.44	505
weighted avg	0.87	0.90	0.88	505





5. Conclusion

These results have validated that deep learning models are better than traditional machine learning models in image analysis. Due to the class imbalance in the dataset, the SVM and Custom-made CNN models perform exceptionally well on the "mild" class but struggle with "severe" and "moderate" classes achieving accuracy of 89% and 90% respectively. This study showed that Custom-made CNN models performed well in the classification of Lumbar Spinal Stenosis.

6. Recommendations

Ensemble Machine learning and Deep learning models should be trained, cross-validation should be implemented to ensure the performance of the models is consistent across another subset of data. SMOTE can be adopted for data balancing. Grid search should also be adopted for hyper-parameter tuning to get an improved result.

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