Deep Learning for Detection and Severity Classification of Lumbar Spinal Stenosis in MRI Scans

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***Abstract*— The prevalent illness known as lumbar spinal stenosis (LSS), which primarily affects older persons, is brought on by the narrowing of the spinal canal and causes numbness, weakness, and discomfort in the lower limbs. In order to avoid disability Although Magnetic Resonance Imaging (MRI) scan analysis is currently a subjective and time-consuming procedure, early and precise identification of LSS is crucial. In order to automatically identify and categorize the severity of LSS using axial T2-weighted MRI scans, this study suggests a pipeline model which consists of Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. Deeper comprehension of degeneration patterns across several lumbar vertebral levels is made possible by the LSTM network's ability to capture temporal dependencies and the CNN's ability to extract spatial characteristics from MRI images. To estimate the model's performance, it is trained on a labeled dataset of MRI scan, with an emphasis on identifying and categorizing LSS severity at the L4–L5 level. The validation accuracy plateaued at about 51%, despite gains in training accuracy, suggesting difficulties with generalization. Class imbalance, a lack of training data, and data complexity are some of the potential causes of these difficulties. The results suggest potential underfitting, despite the experiment's encouraging application of deep learning techniques for automated LSS identification and classification. This model presents a viable strategy to improve diagnostic effectiveness in LSS classification and detection.**

Keywords*— *Lumbar Spine Stenosis (LSS), DICOM Images, MRI Scans, Axial T2-weighted MRI, Spinal Canal Narrowing, Subarticular Stenosis, LSTM, CNN.

I. INTRODUCTION

The lumbar spine is positioned in the lower segment of the spinal cord., helps balance the body's weight [1]. Five robust and flexible vertebrae surround the spinal cord, ensuring that axial forces are distributed evenly [2]. The lumbar spine constitutes bones, cartilage, nerves, and muscles. Each of these components is essential for the creation and function of the lumbar spine [3]. The lumbar spine serves several important tasks, including protection, upper body support, and truncal mobility [4]. The primary goal is to safeguard the nerves and spinal cord. Along with supporting the head, neck, and trunk, it also bears the weight of the upper body [1].The issues in lumbar spine can cause the condition such as spinal stenosis, herniated disks,etc. which leads to discomfort and pain.

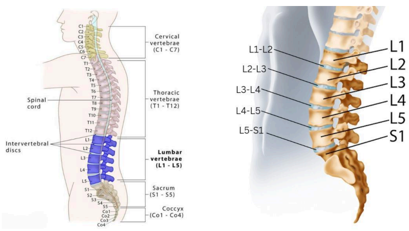

Figure 1 Anatomy of the vertebral column.

The reduction of the lumbar spinal canal caused by degenerative changes of ligaments, intervertebral discs, and joints is commonly referred to as lumbar spinal stenosis [5]. The symptoms of nerve-related discomfort, lower back pain, leg pain radiating down to lower limbs, tiredness, and decreased sensation of the lower limb worsen following standing or walking for a longer time [6]. It causes vertebral hypermobility, increased facet joint pressure, disc space narrowing, and joint enlargement, which collectively contribute to the stenosis. The effects of intervertebral disc degeneration in degenerative lumbar spinal stenosis on all segments of spinal mobility [7]. Typically, MRI assessment of lumbar disc stenosis calls for an experienced radiologist for observation of the morphology of the intervertebral disc in the MRI image, usually paired with sagittal and transverse axial images concurrently [8].

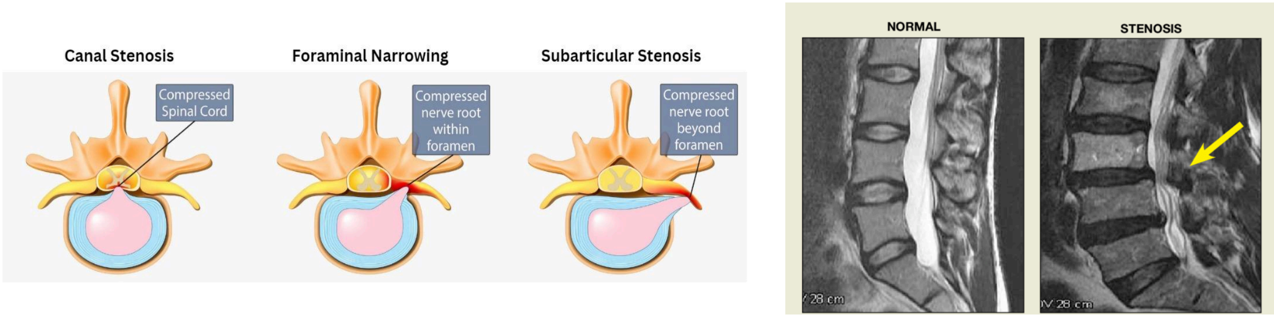

Figure 2 The image illustrates different types of lumbar spinal stenosis and also the normal and stenosis condition of the spine.

In this research, we propose a novel pipeline model that uses convolutional neural network (CNN) and long short-term memory (LSTM) networks to detect and categorize lumbar spinal stenosis severity from Magnetic Resonance Imaging (MRI) images in Digital Imaging and Communications in Medicine (DICOM) format. The model specifically interprets axial T2-weighted MRI data, with an emphasis on the L4-L5 level, a common site for degenerative alterations and stenosis. The CNN component pulls spatial characteristics from images, capturing delicate anatomical details, while the LSTM uses sequential patterns to improve contextual awareness. This hybrid technique attempts to give reliable and automated severity categorization of lumbar spinal stenosis, which could help radiologists make clinical decisions. By using cutting-edge approaches to target a vital anatomical level, the model answers the growing requirement for precision in spinal imaging.

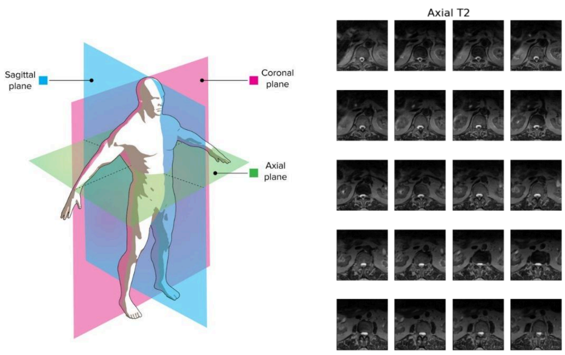

Figure 4 L.H.S shows the Sagittal, Axial and Coronal Plane and R.H.S shows the Axial T2 weighted MRI images.

The paper is organised as follows: Section II reviews the related work that has been carried out earlier on diagnosis of LSS from the MRI images using machine learning and deep learning techniques including research gaps and further scope of improvement. Section III identifies the research gaps and challenges. Section IV proposes the methodology that is used in this project. Section V presents an analysis of the model's performance along with the collected results. Section VI presents the discussion on performance of the model and also the techniques that can be implemented in future for the better performance of the model. Section VII concludes the work.

II. RELATED WORK

Deep learning development has changed everything related to lumbar spinal stenosis identification, segmentation, and severity classification based on MRI images, transforming all into fully scalable and efficient solutions superior to any manual approach. The pioneering research of Meghavi Rana et al. [9] had proved superiority of DL compared to the conventional ML technique in that DL manages large amounts of data and brings forth intricate features. Similar to this, Mengfang Li et al. [10] demonstrated the great performance of CNNs, RNNs, and GANs in extracting hierarchical spatial feature extraction for the diagnosis of LSS. The additional developments are by Chao Hou et al. [11] who have the semi-supervised model which made use of pre-training and fine-tuning for generalization improvement over imaging methods. With ResNeXt101 for classification combined with Faster R-CNN for region identification, Weicong Zhang et al. [12] managed to achieve 87.7% detection accuracy. Mohammad Alsmirat et al. [13] also improved the diagnostic reliability using methods such as fixed cropping and ROI extraction in preprocessing. Y. Ishimoto et al. [27] developed a reliable grading system called SpineNet that is close to the expert's consensus but requires further validation to be used for treatment planning and grading. Guoxin Fan et al. [28] demonstrated the potential for improved surgical planning using the ML classifiers with CT myelography to make accurate predictions with the ROC-AUC over 0.90. All these findings suggest that DL has revolutionized LSS diagnostics, relieving the burden on radiologists and increasing accuracy and facilitating individualized treatment plans.

III. RESEARCH GAPS

The research gaps in automatic LSS detection and classification-recognized gaps are that models would be limited by their dependency on specific MRI modalities, like T2-weighted images-and are not strong in a large variety of situations in radiology. Lack of standardized datasets hampers benchmarking and comparison of research. Further development is hindered by the availability of limited labeled data for severity classification, which is laborious to annotate manually. The detection-focused research dominates the studies on severity classification, which are important for developing treatment strategies for each patient. Deep learning models are a "black box," and XAI approaches are needed. The results are often not able to meet the computational and temporal requirements necessary for clinical setups. Scalability and real-time applications are understudied. Major gaps in DL models include improved generalizability, standardization of datasets, and scalability. These need to be addressed before DL models are integrated into routine clinical workflows. [9]-[28].

IV. METHODOLOGY

A. Data Collection

The first phase of the project involves data collection, which includes lumbar spine MRI scans in DICOM format, accompanied by annotation files in CSV format. RSNA 2024 Lumbar Spine Degenerative Classification Dataset [29] was used as the primary data source, providing MRI scans and associated severity annotations. These annotations include severity labels, Region of Interest (ROI) coordinates, and MRI series descriptions. Generally, MRI sequences, Axial T2-weighted scans are preferred as they well represent the sequences that help to visualize subarticular stenosis [30]. Also, the distributions of the severity classes of subarticular stenosis at the L4-L5 level have a well-balanced distribution of Normal/Mild, Moderate, and Severe levels. DICOM images are pre-processed to the size of 128x128 pixels and normalized between [0, 1] pixel values to have uniform sizes for training models.

B. Model Architecture

The core of the methodology is a CNN-LSTM hybrid model [31] designed to leverage both spatial and sequential features of MRI scans. The convolutional neural network (CNN) is responsible for extracting hierarchical spatial features from each MRI slice by a series of convolutional and max-pooling layers, which is then further reduced in dimension with the help of Global Average Pooling to retain the most significant spatial features. This CNN model is then enveloped in a TimeDistributed layer to process multiple MRI slices as a sequence while preserving spatial information for each slice. The LSTM (Long Short-Term Memory) network is also introduced to capture temporal dependencies between consecutive slices,so that the model learns contextual relationships between adjacent slices, which is therefore important to estimate the degree of stenosis. The output from LSTM passes through fully connected dense layers with ReLU activation followed by a softmax layer to perform multi-class classification on the severity level of stenosis.

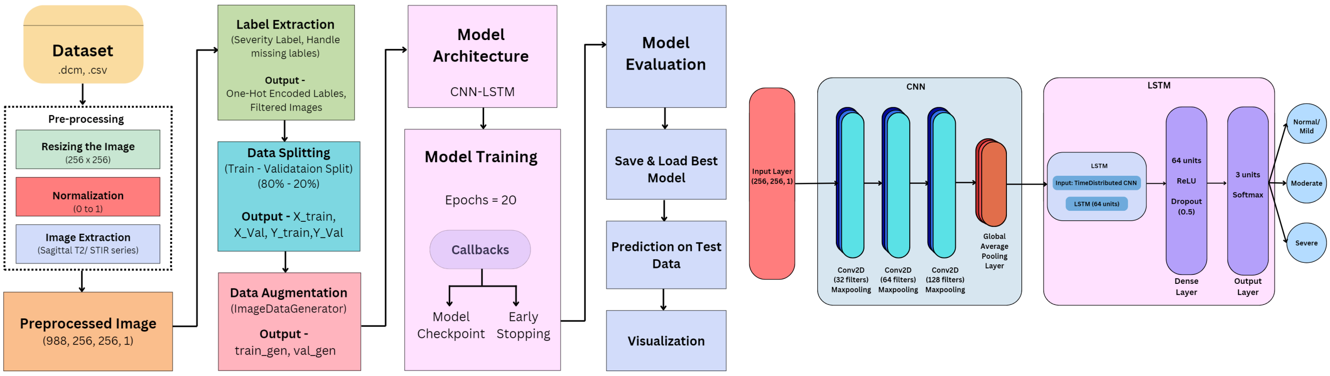

Figure 5 Block Diagram of CNN-LSTM Workflow and CNN - LSTM Model Architecture

C. Training and Validation

Model training is carried out with the Adam optimizer with a learning rate of 0.0001 [32], and categorical cross-entropy as the loss function to handle multi-class classification. The dataset is split with an 80:20 ratio for both the training and validation sets to make sure that the model is tested on unseen data. Data augmentation techniques [33] such as rotation, zoom, and horizontal flipping are applied to balance the dataset and improve generalization, especially for the less-represented Moderate and Severe categories. To prevent overfitting, callbacks are used, including ModelCheckpoint to save the best-performing model and EarlyStopping to halt training if no improvement is observed over several epochs. Evaluation is done using standard metrics such as accuracy, precision, recall, and F1-score, and training and validation loss curves are analyzed to detect overfitting.

D. Severity Classification

After training, the model performance is evaluated through a test set consisting of MRI images with varying severity levels of left subarticular stenosis. The model predicts the severity of the stenosis as Normal/Mild, Moderate, or Severe. The final output includes a classification report, confusion matrix, and visualizations of accuracy and loss curves [34]. The model's output also provides an interpretation, stating the detected type of stenosis, its lumbar level, and its severity. This entire classification process leads to an accurate diagnosis of lumbar spinal stenosis, contributing to improved clinical decision-making.

V. RESULT

The deep learning model, specifically a hybrid CNN-LSTM architecture, was trained on axial T2-weighted MRI scans for the task of classifying the severity level of left subarticular stenosis at L4-L5. The training process spanned 20 epochs, but early termination was implemented based on the convergence of validation loss using the EarlyStopping callback. Several key observations were made during the training and validation phases.

A. Training and Validation Accuracy

The training started with an initial accuracy of 41.41% and gradually improved, reaching a peak of 51.03% by the 12th epoch. During the validation phase, accuracy stabilized at approximately 51.09%, indicating minimal improvement after the early epochs. The consistent validation accuracy suggests that the model struggled to generalize beyond this point, revealing a possible problem with capturing the correct distinctions between severity classes by the model.

B. Training and Validation Loss

The model began with a training loss of 1.0974, which steadily declined to approximately 1.0333 by the 8th epoch, indicating effective learning and weight adjustment during the initial stages. Similarly, the validation loss started at 1.0878 and decreased to around 1.0358 by the 6th epoch. However, this decrease plateaued thereafter, suggesting that the model's learning may have reached its limit, which possibly is due to data complexity or even class distribution challenges inherent in the data.

VI. DISCUSSION

The consistent validation accuracy of 51.09% suggests several potential factors affecting the model's performance. One likely cause is class imbalance, despite efforts to augment the dataset. This imbalance might have led the model to focus on classifying the majority class (Normal/Mild), making it difficult to differentiate the more subtle variations in severity levels. Additionally, the limited number of epochs (20 epochs) might have been insufficient for the hybrid CNN-LSTM model to fully capture both the spatial and temporal dependencies within the MRI data, particularly in relation to the finer distinctions between Moderate and Severe stenosis.

The relatively small gap between training and validation loss suggests that overfitting was not a major issue. However, the model might be suffering from underfitting, where the complexity of the model or the data augmentation techniques used need further refinement. This underfitting could be due to a mismatch between the model architecture's capacity and the complexity of the data, requiring a more sophisticated approach to capturing the necessary features.

Despite the balanced distribution of severity classes in the L4-L5 subarticular stenosis dataset, the model's failure to exceed an accuracy of 51% indicates the inherent difficulty in distinguishing between different severity levels based on MRI images alone. This suggests that while the model learned some basic features, it struggled with more subtle visual distinctions necessary for classifying the severity of stenosis accurately.

The modest performance gain throughout training highlights potential areas for improvement. The architecture may need further adjustments, particularly in how the temporal features from consecutive MRI slices are learned and integrated. Enhancing the data preprocessing, augmentation strategies, or extending the number of training epochs could help the model achieve better generalization and improved performance in future iterations.

VII. CONCLUSION

This project aimed to develop a hybrid CNN-LSTM model for classifying the severity of left subarticular stenosis at the L4-L5 level using axial T2-weighted MRI scans. Despite improvements in training accuracy, the model's validation accuracy plateaued at around 51%, likely due to challenges such as class imbalance, insufficient training data, and data complexity. The findings suggest an underfitting model case, yet highlight the potential development, especially concerning deep learning techniques in medical image analysis for stenosis detection and classification.

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