Automated X-Ray Image Analysis for Lumbar Spondylolisthesis Detection and Severity Grading

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Abstract

Spondylolisthesis, characterized by the anterior displacement of a vertebra, significantly impacts spinal health diagnosis and treatment. This study introduces a groundbreaking machine learning strategy for automated detection and grading of lumbar spondylolisthesis from X-ray images, utilizing Roboflow for data management and a customized convolutional neural network (CNN). This CNN accurately identifies lumbar vertebral segments and objectively grades vertebral slippage. The evaluations show a mean average precision (mAP) of 98.5%, with precision at 96.8% and recall at 97.2%, underscoring the model's accuracy and reliability. Additionally, we developed a user-friendly interface for healthcare professionals, enhancing the tool's clinical applicability. The method offers a significant improvement over existing diagnostic approaches, providing a reliable, efficient solution for the early detection and management of lumbar spondylolisthesis.

Keywords: Lumbar Spondylolisthesis, P-Grade, Spine, Lumbar Vertebrae Classes

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1. Introduction

Lumbar Spondylolisthesis is a medical condition where one of the vertebrae in the lower back slips forward or backward relative to the adjacent vertebrae, leading to a range of health issues such as chronic back pain, reduced spinal flexibility, nerve compression, and potentially severe neurological impairments. The lumbar region, which includes the five lower vertebrae of the spine, is particularly susceptible to this condition due to its role in bearing the body's weight and enabling movement.

The condition manifests in several forms:

Isthmic Spondylolisthesis: Often stemming from a defect or fracture in the vertebra's pars interarticularis, this type typically develops during adolescence but may not become apparent until later [10, 12].

Degenerative Spondylolisthesis: This type is generally associated with age-related changes such as the weakening of discs and ligaments, predominately observed in older adults [9, 14].

Traumatic Spondylolisthesis: Resulting from acute trauma, this type causes sudden vertebral slippage [12, 15].

Diagnosing lumbar spondylolisthesis involves clinical evaluation and imaging, with X-rays commonly used to assess vertebral alignment and slippage. A crucial diagnostic element is determining the slippage grade, based on the Meyerding classification [11], which ranges from Grade I (mild) to Grade V (complete slippage). Table 1 correlates P-grades with the degree of vertebral slippage, where P-grades below or above 50% indicate mild or severe slippage, respectively, and a P-grade over 100% signifies total spinal slippage, indicating the most severe case of the disorder. The Table.1 illustrates the Vertebral Slippage Classification

Table 1. Vertebral Slippage Classification.

P-Grade (A/B)	%	Description
Grade 1	0–25%	Low grade
Grade 2	26–50%	
Grade 3	51–75%	High grade
Grade 4	76–100%	
Grade 5	Complete dislocation of vertebral body (>100%)	Spondyloptosis

Manual examination of X-ray images for signs of lumbar spondylolisthesis can be time-consuming and subjective, depending on the expertise of radiologists. To address these challenges, machine learning and computer vision provide potent tools for automating the detection and grading of spondylolisthesis. These technologies enhance accuracy, decrease diagnostic time, and ensure consistent results. Figure 1 offers an illustrative representation of vertebral slippage, showcasing how these advancements can be visualized and applied.

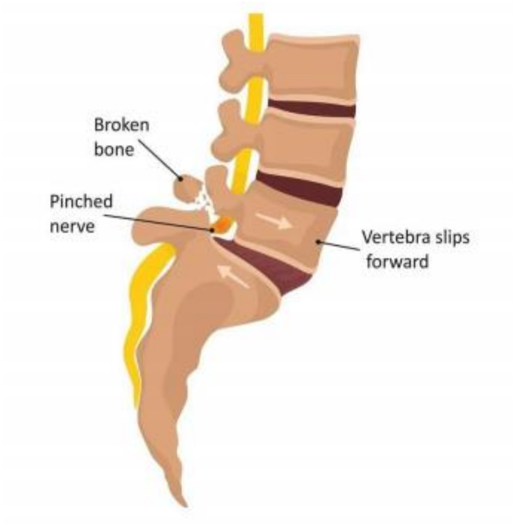

Figure 1. Illustrative Representation of Vertebral Slippage.

Addressing the complex challenge of detecting Lumbar Spondylolisthesis from X-ray images requires overcoming significant obstacles in medical imaging, notably the need for high diagnostic precision. Traditional methods often miss subtle yet critical indicators of this condition, leading to delays in diagnosis and suboptimal patient outcomes. This research seeks to revolutionize the approach by employing deep learning to enhance the sensitivity and specificity of detection and establish a robust basis for early intervention and tailored treatment strategies. The goal is to transform spinal health diagnostics, thus ensuring more accurate diagnoses, enabling timely interventions, and ultimately improving patient well-being.

This research is driven by the limitations of existing diagnostic techniques, which struggle to capture the nuanced features characteristic of Lumbar Spondylolisthesis. By integrating deep learning, this research aims to explore the depths of X-ray imaging to create a significant paradigm shift in spinal health diagnostics and patient care. The primary objectives and approach of this research include:

1. **Developing a Robust Detection Model:** Construct an object detection model that accurately identifies the presence of lumbar spondylolisthesis in X-ray images.

2. **Algorithm for Grading Severity:** Design an algorithm capable of calculating the grade of vertebral slippage, providing a consistent and objective assessment of the condition's severity.

3. **Performance Evaluation:** Conduct thorough testing of the model and algorithm to ensure reliability and accuracy in real-world scenarios.

4. **User-Friendly Interface Development:** Develop an intuitive interface tailored for healthcare professionals, enhancing usability and accessibility.

This comprehensive approach promises to enhance the tools available to healthcare professionals, facilitating more informed decision-making and fostering better patient outcomes. The report outlines our methodology, experimental results, and conclusions, offering insights into future developments in this critical area of healthcare.

2. Related Work

This review examines recent advancements in medical imaging technology, particularly focusing on the role of deep learning in enhancing diagnostic accuracy and automation. It highlights various deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), and their applications in analyzing different types of medical images including X-rays, MRI, and CT scans. The survey addresses challenges such as the scarcity of labeled datasets and the need for interpretable models in medical contexts, while also exploring the integration of these algorithms into clinical workflows. Additionally, it discusses the potential of transfer learning and domain adaptation in improving the generalization of models across different patient populations and imaging environments. By offering a critical review of the literature and identifying gaps, this survey aims to advance AI applications in healthcare, specifically in the detection and management of musculoskeletal disorders like lumbar spondylolisthesis, ultimately facilitating the development of robust diagnostic tools that enhance clinical practices and patient outcomes.

Trinh et al. [1] created LumbarNet, a U-Net-based CADx algorithm enhanced with a feature fusion module, achieving 88.83% accuracy and superior vertebral slip detection in lumbar X-rays, demonstrating its reliability over traditional U-Net.

Zhang J et al. [2] introduced a deep learning model using Faster R-CNN for detecting lumbar spondylolisthesis from X-rays, outperforming orthopedic surgeons and radiologists with better precision, recall, and F1-score. The model also improved diagnostic accuracy and reduced diagnosis time.

Varçın et al. [5] developed a Yolov3 and MobileNet CNN-based transfer learning model for lumbar X-ray analysis, achieving 99% accuracy with high sensitivity and specificity, suggesting strong potential for use in outpatient clinics with limited expert availability.

Saravagi et al. [7] combined VGG16 with Capsule Network in an integrated model (S-VCNet) for lumbar spondylolisthesis diagnosis, demonstrating 98% accuracy and efficient positional structure capture, and deployed on the Gradio web app for quick radiological assessments.

Deepika Saravagi et al. [8] implemented a model simplification via weight and unit pruning, retaining high diagnostic accuracy (94.12%) while drastically reducing the computational load, suitable for deployment on resource-limited devices.

Ruchi et al. [16] used advanced feature extraction and selection methods, including Spider Monkey Optimization and a linearity-based CNN, achieving high classification accuracy (up to 96%) for lumbar disorders in MRI datasets.

Fraiwan M et al. [19] employed deep transfer learning to diagnose spondylolisthesis and scoliosis from X-rays without explicit measurements, achieving over 96% accuracy in classifications, aiding in accurate, early diagnosis.

Tran et al. [20] developed MBNet, a multi-task deep neural network using a multi-path CNN architecture for semantic segmentation and shape detection in lumbar X-rays, achieving superior segmentation accuracy and effective lumbar vertebrae and sacrum analysis.

Varçın et al. [4] explored the use of AlexNet and GoogleLeNet for diagnosing spondylolisthesis from X-rays, analyzing 272 images equally split between affected and normal cases. GoogleLeNet achieved a higher accuracy of 93.87%, compared to AlexNet's 91.67%, demonstrating its potential for supporting diagnoses in clinics with limited access to experienced doctors.

Saravagi et al. [3] utilized VGG16 and InceptionV3 models for detecting spondylolisthesis in X-rays, enhancing the dataset to 299 images via augmentation. The optimized VGG16 model reached 100% accuracy after TFLite compression, outperforming InceptionV3's 96% and excelling in diagnostic capability across multiple datasets.

Lehnen et al. [6] used a CNN to diagnose lumbar spine degenerative changes in MRI scans of 146 patients, achieving high diagnostic accuracy, particularly in disc labeling and detection of spinal stenoses and nerve compressions.

Kim et al. [18] developed a deep learning model for segmenting vertebral bodies in lateral spine images to measure vertebral compression ratios accurately. Testing on 339 images, the model achieved a sensitivity of 0.937, specificity of 0.995, and accuracy of 0.992, with high statistical agreement to manual measurements by specialists.

Klinwichit et al. [17] introduce BUU-LSPINE, a dataset of 3600 lumbar spine X-rays annotated for spondylolisthesis research. Using models like YOLOv5 and SVM, the study achieved high accuracy in vertebrae detection and spondylolisthesis prediction, highlighting its potential for clinical decision support system development.

This comprehensive review underlines significant strides in the integration of deep learning technologies in medical imaging, particularly for the diagnosis and management of lumbar spondylolisthesis. Across various studies, deep learning models like U-Net, Faster R-CNN, YOLOv3, and MobileNet have not only matched but often exceeded traditional diagnostic accuracy, showcasing their potential in enhancing clinical workflows and patient care. Particularly notable is the use of transfer learning and algorithm optimization to adapt these technologies for real-world clinical applications, ensuring that they can be deployed effectively even in resource-limited settings. As these technologies continue to evolve, they promise to revolutionize the field of medical diagnostics, making advanced diagnostic tools more accessible and reliable across different healthcare environments.

3. Proposed Methodology

The proposed methodology for automating the diagnosis and severity grading of lumbar spondylolisthesis involves using an object detection model and various deep learning techniques supplied by Roboflow. These are used for detecting the presence of lumbar spondylolisthesis and classifying different lumbar vertebrae. Subsequently, an algorithm is implemented to determine the percentage of slippage of the upper vertebra over the lower vertebra, which is used to calculate the severity grade of the lumbar spondylolisthesis.

3.1 Dataset

For the diagnosis and management of spinal disorders like spondylolisthesis, the BUU-LSPINE dataset introduced by Klinwichit et al. [17] plays a crucial role. This dataset includes approximately 3600 lateral x-rays specifically of patients diagnosed with spondylolisthesis. To maximize its utility for developing robust diagnostic models, we implemented advanced data augmentation techniques that significantly expanded the dataset size and enhanced model performance. These techniques simulated clinical variabilities through geometrical modifications like rotation, scaling, and flipping, along with adjustments to brightness and contrast to address variations in film exposure common in radiographic practices. The augmented dataset not only facilitated a broader training scope on varied image features and anomalies, helping to mitigate overfitting but also improved the models' generalization to real-world conditions. As a result, the enhanced dataset led to higher accuracy in vertebral detection, corner point extraction, and spondylolisthesis prediction, enhancing the models' robustness and reliability for clinical application. This effort highlights the critical importance of diverse, high-quality training data in developing effective AI-based diagnostic tools in medical imaging.

3.2 Architecture Diagram

The proposed system, depicted in Figure 2, automates the detection and grading of lumbar spondylolisthesis in X-ray images through a robust process that begins with the collection of spinal X-ray data. This dataset is enhanced with various augmentation techniques to increase its size and diversity, followed by detailed annotation of the presence and severity of spondylolisthesis. At the core is an object detection model that, after rigorous training on these annotated images, can identify patterns indicative of lumbar spondylolisthesis in new, unseen X-ray images. The model’s effectiveness is evaluated using a separate dataset to ensure accuracy and generalizability. For user interaction, the system includes a user-friendly interface where X-ray images can be uploaded for analysis, with results indicating the presence and grading of spondylolisthesis provided in real-time. The system is designed for potential integration into web servers or cloud platforms, allowing remote access by healthcare professionals, thereby streamlining the diagnostic process and enhancing both efficiency and accuracy in real-world scenarios.

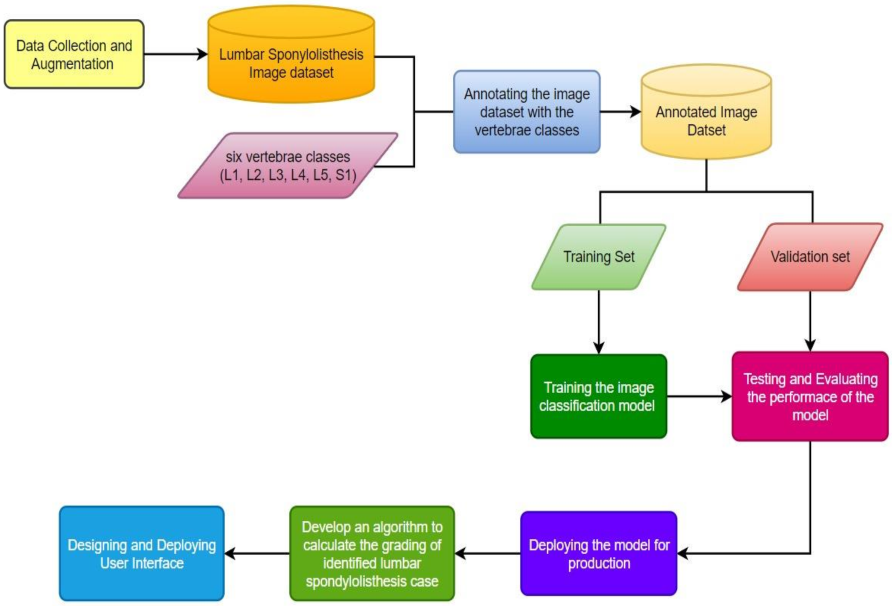

Figure 2. Architecture Diagram of Proposed Lumbar Spondylolisthesis Detection System.

3.3 Roboflow Model for Diagnosis

Integrating Roboflow into the research has significantly enhanced the management, training, and deployment of an object detection model designed to diagnose and grade lumbar spondylolisthesis using X-ray images. The process begins with the careful collection and augmentation of a dataset of lumbar spine X-ray images, addressing the challenge of limited dataset sizes highlighted in prior research. Roboflow's advanced data augmentation capabilities ensure the dataset is reflective of the varied clinical scenarios encountered in practice. Central to the research is the training of a convolutional neural network (CNN), with Roboflow facilitating seamless integration with top deep learning frameworks, aiding in model architecture selection, hyperparameter tuning, and ensuring optimal learning through an iterative training process.

Roboflow's role extends to the precise annotation of images, marking regions from vertebrae L1 through S1, which is essential for training the model to recognize and classify different degrees of vertebral displacement. The organized dataset is then split into training, validation, and test sets to support robust model evaluation, providing critical metrics such as sensitivity, specificity, and accuracy, as shown in Figure 3. These metrics are vital for establishing the clinical efficacy of the model. Once validated, the model is deployed using Roboflow's infrastructure, enabling integration into a web-based interface for real-time analysis by healthcare professionals. This interface facilitates immediate lumbar spondylolisthesis detection and grading based on vertebral displacements. Additionally, Roboflow supports continuous learning, allowing the model to be periodically updated with new data, ensuring it remains aligned with evolving clinical insights and diagnostic standards.

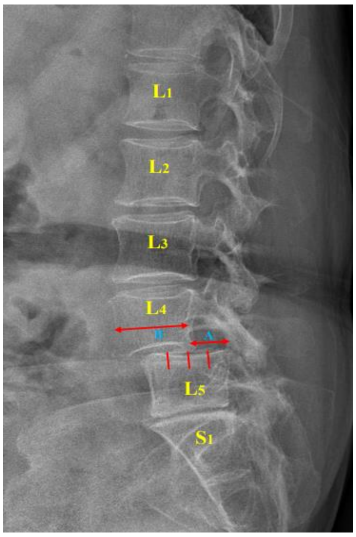

Figure 3. Classification of the various Vertebral Classes and Identification of Slippage [4]

In summary, by leveraging Roboflow, the research not only addresses significant limitations noted in prior studies—such as dataset size and lack of detailed grading—but also ensures that the system developed is scalable, effective, and continually improving. This integration highlights the transformative potential of combining advanced object detection models with powerful data management and augmentation platforms like Roboflow in medical imaging diagnostics.

3.4 P-Grade Calculation

The severity of the lumbar spondylolisthesis that is present or the percentage of the amount of slippage of the upper vertebrae with respect to the lower vertebrae can be identified by calculating the P-grade of slippage with gives the severity grading of the lumbar spondylolisthesis. The calculation of the P-grade is explained below.

As a whole, the lumbar region is composed out of 5 lumbar vertebrae. Each vertebral quadrilateral (Li), for its part, includes the points that are far at opposite sides of the quadrilateral (i = 1, 2, 3, 4, or 5). These four extreme points which are known simply as pLi1, pLi2, pLi3, and pLi4 for the upper-left, upper-right, lower-right, and lower-left points of a lumbar vertebra are the areas of interest. The four points of each vertebra are arranged in a counter clockwise direction beginning at the upper left. Figure 4 shows that the sacrum's upper plate is represented by two points: left psacral1 and right psacral2.

The technique calculates P-grades for L1-L2, L2-L3, L3-L4, L4-L5, and L5-S1 levels and verifies if they exceed K1, as outlined in the equations below:

$$f_{pgrade}(m,n) = p_{grade}(i,j) > K1, \qquad (1)$$

$$p_{grade}(i,j) = \frac{D(P_{i,proj}, P_{j,2})}{\sqrt{\|P_{j,1} - P_{j,2}\|^2}}, \qquad (2)$$

$$D(P_{i,proj}, P_{j,2}) = \sqrt{\|P_{i,proj} - p_{j,2}\|^2} \qquad (3)$$

The indexes i and j correspond to the proximal vertebral regions i ∈(L1, L2, L3, L4, L5) and j ∈ (*L2, L3, L4, L5, S1*) and f_{pgrade} represents the shift value of the lower plate of the i_{th} lumbar vertebra relative to the upper plate of the j_{th} lumbar vertebra.

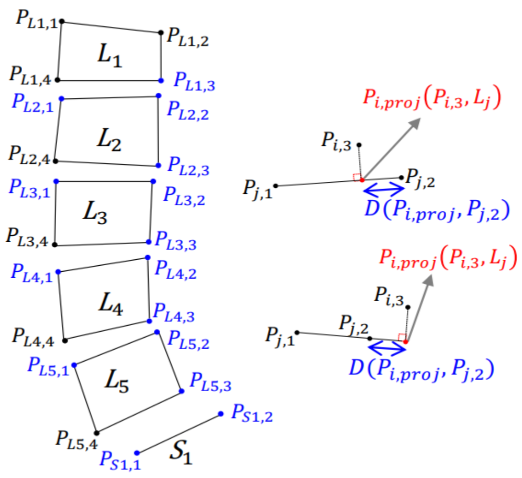

Figure 4. Illustration of Lumbar Vertebrae Classes with Corresponding Bounding Boxes and Extreme Points. [4]

The procedure determines the projected point pproj between pi,3 and line Lj, with end points pj,1 and pj,2. The distance (Dpi,3,Lj) between the projected point and upper right point (pj,2) of the j-th lumbar vertebra is computed. Additionally, f pgrade is calculated by dividing D(Pi,proj, Pj,2) by the upper-plate length of the j-th lumbar vertebra, as evidenced by Figure 4. The projected point is either within or beyond the segmented line indicating the top plate of the j-th lumbar vertebra.

3.5 Pseudocode for Detecting Vertebral Slippage using Meyerding's Grading System

i. Input: Lumbar X-Ray image.

ii. Preprocess Image:

- Emphasize important features within the image.
- Resize the image to a standard resolution suitable for analysis.

iii. Inference using LumbarNet:

- Apply the deep learning model, LumbarNet, to detect lumbar features in the resized image.

iv. Restore Image Size:

- Resize the processed image back to its original resolution to maintain accuracy in spatial measurements.

v. Feature Detection and Analysis:

- Detect critical lumbar features including vertebral edges and key points.

vi. Fit Quadrangle to Lumbar Vertebrae:

- Fit a geometric quadrangle based on detected vertebral features to approximate the shape of each vertebra.

vii. Calculate P-grade for each vertebral pair (L1-L2, L2-L3, L3-L4, L4-L5, L5-S1):

- For each vertebra i and its adjacent vertebra j:

a. Calculate the projected point p_proj on the line L_j using the formula:

p_proj = intersection of line L_j and a perpendicular from point pi,3 (of vertebra i).

b. Calculate distance D(Pi,proj, Pj,2) using:

D(Pi,proj, Pj,2) = distance between p_proj and pj,2.

c. Calculate p_grade(i, j) using:

p_grade(i, j) = (D(Pi,proj, Pj,2) / length of the upper plate of vertebra j) * 100.

viii. Classify Slippage Using Meyerding's Grading:

- For each calculated p_grade(i, j):

a. Determine the Meyerding grade based on p_grade(i, j):

- Grade I: 0-25%

- Grade II: 25-50%

- Grade III: 50-75%

- Grade IV: 75-100%

- Grade V: > 100% (spondyloptosis)

b. Classify the severity of slippage accordingly.

viii. Output:

- For each vertebral pair, output the slippage classification and the corresponding Meyerding grade.

4. Simulation Results

The user interface was linked to the backend and to the Roboflow object detection model using the API and was simulated to ensure that the research was working as ensured.

The model was provided with the X-ray image of a spine in order to detect the presence of lumbar spondylolisthesis in that spinal image. The image can be uploaded to the model through the user interface as shown in Figure 7. The model than analyses the uploaded image to detect the presence of lumbar spondylolisthesis in it. If the presence of lumbar spondylolisthesis is detected and confirmed, the model identifies the pair of vertebrae where the slippage of vertebrae has occurred and that region is highlighted on the uploaded X-ray image and id displayed to the user as depicted in the Figure 5.

Figure 5. Anatomical Representation of Lumbar Spondylolisthesis Location.

Figure 6 displays the highlight of the all six lumbar vertebrae using bounding boxes of different colours along with their class label so that the user gets a clear picture of the occurrence of lumbar spondylolisthesis that is the user gets an idea of where actually the lumbar spondylolisthesis has occurred and among which pair of lumbar vertebrae the slippage has occurred that has caused the occurrence of lumbar spondylolisthesis.

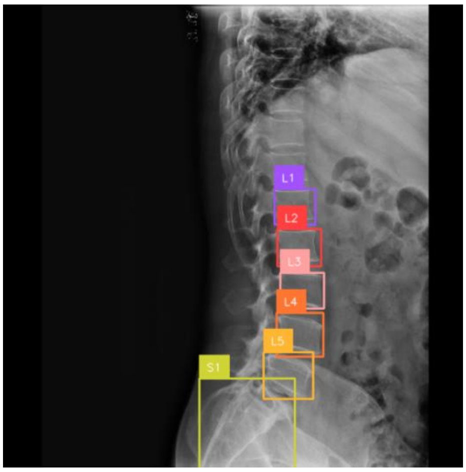

Figure 6. Model-Predicted Bounding Boxes on Vertebral Column Bones.

Figure 7 showcases the system's dashboard interface, tailored for healthcare professionals. Through this interface, doctors can log in, upload spinal X-ray images, and receive a concise report. This report provides crucial diagnostic information, indicating whether lumbar spondylolisthesis is present, identifying the specific vertebrae involved, and detailing the percentage of slippage and the severity grade. The frontend of this application is developed using HTML, CSS, and Django to ensure a user-friendly experience, while MySQL is utilized for backend database management, facilitating efficient data handling and storage.

Figure 7. Consolidated Report of X-ray Image Analysis.

5. Performance Evaluation and Analysis

The proposed model has been rigorously tested to evaluate its performance in classifying different vertebral bones using two distinct datasets: a validation set and a test set. The primary goal was to identify the precision of the model across multiple classes, specifically the five lumbar vertebrae (L1, L2, L3, L4, L5) and the first sacral vertebra (S1).

5.1. Average Precision by Class

In the validation set, the proposed model achieved an overall average precision of 93%, with individual scores of 93% for L1, 91% for L2, 90% each for L3 and L4, 92% for L5, and a perfect score of 100% for S1. This indicates a robust performance across all classes, particularly highlighting the model's effectiveness in accurately identifying the sacral region. Comparatively, the test set demonstrated even higher precision, with an overall average of 98%. The precision for individual classes was 96% for L1, 98% for L2, 99% for both L3 and L4, 99% for L5, and 99% for S1, showcasing exceptional accuracy, especially in the lumbar region from L3 to L5.

Figure 8 illustrates the model's predictions across different classes of vertebral bones, showing how the precision percentages vary slightly among the classes in a practical scenario. The precision rates are 88% for L1, 92% for L2, 91% for L3, 89% for L4, 89% for L5, and 90% for S1. Despite some variability, these results are indicative of high performance, suggesting that our model can reliably identify different vertebral bones under diverse conditions.

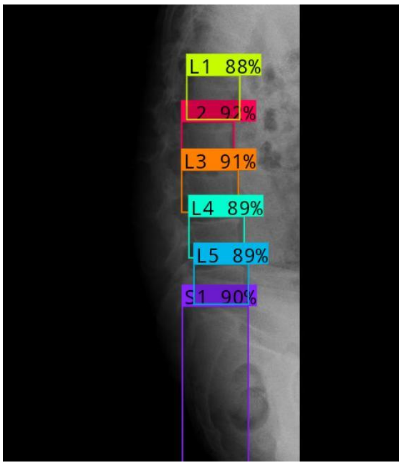

Figure 8. Precision of Vertebral Bone Classification by Class.

5.2. Comprehensive Performance Metrics

To offer a comprehensive assessment of our model's effectiveness, we computed the mean Average Precision (mAP) at 98.5%, achieving an overall precision rate of 96.8% and a recall rate of 97.2%. These statistics underscore the model's high dependability and robustness in classifying vertebral conditions and demonstrate its accuracy in real-world settings.

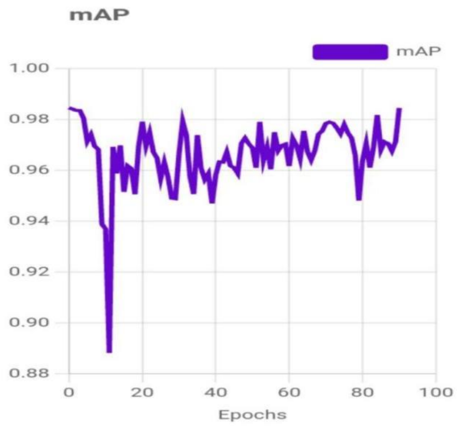

Figure 9. Mean Average Precision (mAP) Trend Over Training Epochs.

The observed training behavior of our model, as illustrated in Figure 9, reveals an intriguing pattern of precision across the epochs. Notably, a temporary dip in precision around the 15th epoch is followed by a significant rebound, with precision stabilizing between 94% and 98% subsequently. This fluctuation suggests a critical adjustment phase where the model fine-tunes its parameters, enhancing its generalization capabilities from the training data. This adaptive response in training demonstrates the robustness of our algorithm, capable of dynamically adjusting to the complexities of the dataset.

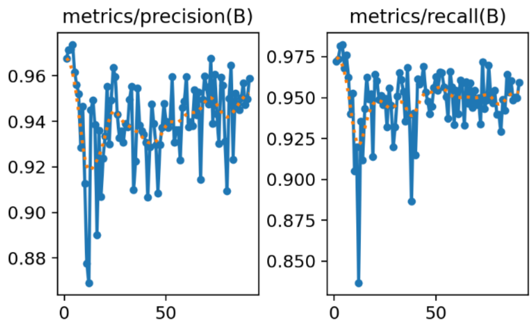

Figure 10. Precision and Recall Trend Over Training Epochs.

Figure 10, which simultaneously tracks precision and recall, mirrors this behavior, marking a concurrent dip and recovery around the same epoch. This synchronized improvement in both metrics not only emphasizes a consistent learning curve but also assures a balanced model performance, adept at accurately identifying relevant instances while minimizing false negatives. This pattern indicates a well-optimized learning process where temporary reductions are effectively utilized to achieve greater predictive accuracy and reliability.

In conclusion, the performance analysis of our model demonstrates its strong capability in the classification of vertebral bones. Despite a brief reduction in precision and recall around the 15th epoch, the model exhibits significant resilience, not only recovering but also maintaining high levels of both metrics thereafter. The stable precision of 94% to 98%, along with a balanced recall, confirms the reliability and accuracy of our model, making it a valuable tool for clinical decision support. This validation of performance bolsters confidence in the model's utility in real-world clinical settings, underscoring its potential to enhance healthcare outcomes significantly.

5.3 Comparative Analysis of Proposed Model with the Available Models

In this section, we conduct a comparative review of our newly proposed model designed for the detection and grading of lumbar spondylolisthesis using X-ray imagery, relative to various well-established models in the domain. Table 2 summarizes the principal outcomes and performance indicators of these models, highlighting their methodologies, diagnostic effectiveness, and precision.

Table 2. Comparative Analysis of Spondylolisthesis Detection Models.

No.	Study	Major Finding	Spondylolisthesis Diagnosis	Grading	Performance Metrics
1.	Saravagi et al. [7]	Utilized VGG16 for feature extraction, followed by CapsNet for detailed analysis.	Yes	No	Accuracy: 98%
2.	Zhang et al. [2]	Utilized Faster R-CNN and RetinaNet, integrating feature extraction, region proposal, and classification for enhanced detection speed and accuracy.	Yes	No	Faster R-CNN:- Precision: 93.5% RetinaNet:- Precision: 79.4%
3.	Trinh et al. [1]	LumbarNet utilizes U-Net with added Feature Fusion Module, Piecewise Slope Detection, and Dynamic Shift for detailed lumbar X-ray analysis.	Yes	No	Accuracy: 88.83%
4.	Saravagi et al. [3]	Optimized VGG16 and InceptionV3 using TFLite for enhanced image classification of X-ray radiographs.	Yes	No	VGG16:- Accuracy: 98% InceptionV3:- Accuracy: 96%
5.	Saravagi et al. [8]	Utilized weight and unit pruning on a CNN to reduce complexity for diagnosing lumbar spondylolisthesis on small devices.	Yes	No	Accuracy: 94.12%
6.	Lehnen et al. [6]	Utilized a CNN to analyze and label multiple MR imaging features of the lumbar spine for detecting degenerative changes.	Yes	No	Accuracy: 87.61%
7.	Varçın et al. [5]	Transfer learning with a fine-tuned MobileNet CNN model and YOLOv3 for ROI extraction from lumbar X-rays.	Yes	No	Accuracy : 99%
8.	Varçın et al. [4]	Used AlexNet and GoogleLeNet neural networks to diagnose spondylolisthesis from lumbar X-ray images.	Yes	No	GoogleLeNet:- Accuracy: 93.87%% AlexNet:- Accuracy: 91.67%
9.	Our Proposed Solution	Utilized Roboflow for data management and a CNN for the detection and grading of lumbar spondylolisthesis from X-ray images.	Yes	Yes	mAP: 98.5% Precision: 96.8% Recall: 97.2%

Our model enhances versatility by combining detection and grading of spondylolisthesis, outperforming existing models in both accuracy and functionality. With high recall and precision, its robustness is well-suited for clinical use. Utilizing Roboflow for efficient data management boosts the model's reliability and accuracy. In conclusion, this model provides a comprehensive tool that could streamline diagnostics and improve spondylolisthesis evaluation, potentially enhancing patient outcomes.

6. Conclusion and Future Work

This research has leveraged Roboflow and deep learning to enhance the automation of diagnosing and grading lumbar spondylolisthesis from X-ray images, overcoming challenges like small dataset sizes and inadequate grading systems. The solution improves diagnostic accuracy and scalability, aiding healthcare professionals in early detection and intervention. Future enhancements could include integrating additional imaging modalities such as MRI and CT scans for a more detailed analysis, adopting adaptive learning algorithms for increased diagnostic precision, and expanding the web interface to integrate with electronic health records for streamlined workflows. Additionally, extending into telemedicine could significantly boost accessibility to quality diagnostics in remote areas, democratizing specialized healthcare services.

References

[1] Trinh, G.M.; Shao, H.-C.; Hsieh, K.L.-C.; Lee, C.-Y.; Liu, H.-W.; Lai, C.-W.; Chou, S.-Y.; Tsai, P.-I.; Chen, K.-J.; Chang, F.-C.; et al. Detection of Lumbar Spondylolisthesis from X-ray Images Using Deep Learning Network. J. Clin. Med. 2022, 11, 5450. https:// doi.org/10.3390/jcm11185450

[2] Zhang J, Lin H, Wang H, Xue M, Fang Y, Liu S, Huo T, Zhou H, Yang J, Xie Y, Xie M, Cheng L, Lu L, Liu P and Ye Z (2023), Deep learning system assisted detection and localization of lumbar spondylolisthesis. Front. Bioeng. Biotechnol. 11:1194009. doi: 10.3389/fbioe.2023.1194009

[3] Deepika Saravagi, Shweta Agrawal, Manisha Saravagi, Jyotir Moy Chatterjee, Mohit Agarwal, "Diagnosis of Lumbar Spondylolisthesis Using Optimized Pretrained CNN Models", Computational Intelligence and Neuroscience, vol. 2022, Article ID 7459260, 12 pages, 2022. https://doi.org/10.1155/2022/7459260

[4] F. Varçin, H. Erbay, E. Çetin, İ. Çetin and T. Kültür, "Diagnosis of Lumbar Spondylolisthesis via Convolutional Neural Networks," 2019 International Artificial Intelligence and Data Processing Symposium (IDAP), Malatya, Turkey, 2019, pp. 1-4, doi: 10.1109/IDAP.2019.8875988.

[5] Varçın, F., Erbay, H., Çetin, E. et al. End-To-End Computerized Diagnosis of Spondylolisthesis Using Only Lumbar X-rays. J Digit Imaging 34, 85–95 (2021). https://doi.org/10.1007/s10278-020-00402-5

[6] Lehnen, N.C.; Haase, R.; Faber, J.; Rüber, T.; Vatter, H.; Radbruch, A.; Schmeel, F.C. Detection of Degenerative Changes on MR Images of the Lumbar Spine with a Convolutional Neural Network: A Feasibility Study. Diagnostics 2021, 11, 902. https://doi.org/10.3390/ diagnostics11050902

[7] Saravagi, Deepika & Agrawal, Shweta & Saravagi, Manisha & Jain, Sanjiv & Sharma, Bhisham & Mehbodniya, Abolfazl & Chowdhury, Subrata & Webber, Julian. (2023). Predicting Lumbar Spondylolisthesis: A Hybrid Deep Learning Approach. Intelligent Automation & Soft Computing. 37. 1-19. 10.32604/iasc.2023.039836.

[8] Deepika Saravagi, Shweta Agrawal, Manisha Saravagi, Md Habibur Rahman, "Diagnosis of Lumbar Spondylolisthesis Using a Pruned CNN Model", Computational and Mathematical Methods in Medicine, vol. 2022, Article ID 2722315, 10 pages, 2022. https://doi.org/10.1155/2022/2722315

[9] Aoki, Y., Takahashi, H., Nakajima, A. et al. Prevalence of lumbar spondylolysis and spondylolisthesis in patients with degenerative spinal disease. Sci Rep 10, 6739 (2020). https://doi.org/10.1038/s41598-020-63784-0

[10] Rangwalla, K., Filley, A., El Naga, A. et al. Degenerative lumbar spondylolisthesis: review of current classifications and proposal of a novel classification system. Eur Spine J (2023). https://doi.org/10.1007/s00586-023-07818-x

[11] Koslosky E, Gendelberg D. Classification in Brief: The Meyerding Classification System of Spondylolisthesis. Clin Orthop Relat Res. 2020 May;478(5):1125-1130. doi: 10.1097/CORR.0000000000001153. PMID: 32282463; PMCID: PMC7170696.

[12] Mohile NV, Kuczmarski AS, Lee D, Warburton C, Rakoczy K, Butler AJ. Spondylolysis and Isthmic Spondylolisthesis: A Guide to Diagnosis and Management. J Am Board Fam Med. 2022 Dec 23;35(6):1204-1216. doi: 10.3122/jabfm.2022.220130R1. Epub 2022 Dec 16. PMID: 36526328.

[13] Chang M, Canseco JA, Nicholson KJ, Patel N and Vaccaro AR (2020) The Role of Machine Learning in Spine Surgery: The Future Is Now. Front. Surg. 7:54. doi: 10.3389/fsurg.2020.00054

[14] El-Daw, Sherif, Ahmad El-Tantawy, Tarek Aly, and Mohamed Ramadan. "Role of machine learning in management of degenerative spondylolisthesis: a systematic review." Current Orthopaedic Practice 32, no. 3 (2021): 302-308.

[15] Li N, Amarasinghe S, Boudreaux K, Fakhre W, Sherman W, Kaye AD. Spondylolisthesis. Orthopedic Reviews. 2022;14(3). doi:10.52965/001c.36917

[16] Ruchi, & Singh, Dr & Singla, Jimmy & Rahmani, Mohammad Khalid Imam & Ahmad, Sultan & Rehman, Masood & Jha, Sudan & Prashar, Deepak & Nazeer, Jabeen. (2023). Lumbar Spine Disease Detection: Enhanced CNN Model With Improved Classification Accuracy. IEEE Access. 11. 141889 - 141901. 10.1109/ACCESS.2023.3342064.

[17] Klinwichit, P.; Yookwan, W.; Limchareon, S.; Chinnasarn, K.; Jang, J.-S.; Onuean, A. BUU-LSPINE: A Thai Open Lumbar Spine Dataset for Spondylolisthesis Detection. Appl. Sci. 2023, 13, 8646. https:// doi.org/10.3390/app13158646

[18] Kim, D.H., Jeong, J.G., Kim, Y.J. et al. Automated Vertebral Segmentation and Measurement of Vertebral Compression Ratio Based on Deep Learning in X-Ray Images. J Digit Imaging 34, 853–861 (2021). https://doi.org/10.1007/s10278-021-00471-0

[19] Fraiwan M, Audat Z, Fraiwan L, Manasreh T (2022) Using deep transfer learning to detect scoliosis and spondylolisthesis from x-ray images. PLoS ONE 17(5): e0267851. https://doi.org/ 10.1371/journal.pone.0267851

[20] Tran, V.L., Lin, HY., Liu, HW. (2021). MBNet: A Multi-task Deep Neural Network for Semantic Segmentation and Lumbar Vertebra Inspection on X-Ray Images. In: Ishikawa, H., Liu, CL., Pajdla, T., Shi, J. (eds) Computer Vision – ACCV 2020. ACCV 2020. Lecture Notes in Computer Science(), vol 12626. Springer, Cham. https://doi.org/10.1007/978-3-030-69541-5_38