Spondylolisthesis Identification in Lumbar Spine Using Centroid Distance Error

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***Abstract*—Spondylolisthesis is a spinal disorder characterized by the anterior displacement of one vertebra over the one beneath it, predominantly affecting the lumbar region. Accurate and timely diagnosis is crucial for effective treatment and patient care. This study proposes an automated method for identifying spondylolisthesis by employing a deep learning approach using SSD for lumbar vertebrae detection. After detecting the vertebrae, the centroids of each vertebra are calculated from their respective bounding boxes, and a linear model is fitted through these centroids to assess vertebral alignment. The centroid distance error, defined as the deviation of each centroid from the fitted line, is utilized to evaluate misalignment indicative of spondylolisthesis. The proposed method was evaluated on a dataset of lumbar spine images, in diagnosing spondylolisthesis based on centroid distance errors. This automated framework demonstrates significant advantages over traditional diagnostic methods, including increased efficiency, consistency, and scalability. The findings highlight the potential of integrating advanced image processing techniques and machine learning models into clinical practice, paving the way for improved diagnostic accuracy and patient outcomes in spinal disorders. Future work will focus on expanding the dataset and exploring the integration of clinical parameters to enhance the model's predictive capabilities. +**

Keywords—Lumbar Spine, Centroid Distance Error, Spondylolisthesis

I. Introduction

Spondylolisthesis is a spinal disorder characterized by the anterior displacement of one vertebra relative to the one below it, commonly affecting the lumbar region [1]. This condition can result in severe complications, including nerve impingement, chronic pain, and restricted mobility, all of which can significantly affect a patient's quality of life. Early diagnosis is essential to prevent further progression and mitigate the symptoms. Typically, the diagnosis is conducted through visual analysis of radiological images, including X-rays, CT scans, or MRI scans, followed by manual measurements of vertebral displacement [2]. While effective, this traditional method suffers from several drawbacks, such as inter-observer variability, the time required for manual inspection, and the potential for human error, leading to inconsistent or inaccurate diagnoses.

In recent years, advances in artificial intelligence (AI) and computer vision have provided opportunities to automate and enhance diagnostic processes, reducing the burden on clinicians and improving diagnostic accuracy. In this paper, we propose an automated approach for detecting and quantifying spondylolisthesis using deep learning techniques, specifically focusing on lumbar spine images. The proposed method integrates the Single Shot Multibox Detector (SSD), a cutting-edge object detection model, to accurately detect and localize individual vertebrae in spinal imaging datasets [3]. The efficiency and accuracy of SSD make it well-suited for real-time applications, as it can effectively handle variations in image quality, orientation, and patient anatomy.

Once SSD detects the vertebrae, the centroids of each vertebra are computed from the bounding boxes. These centroids are crucial for assessing the alignment of the vertebral column. To evaluate the spinal alignment, a best-fit linear regression line is calculated, passing through the centroids of all detected vertebrae. This line serves as the reference for an ideal, healthy spine where no significant misalignment is present. The characteristic of spondylolisthesis is quantified by calculating the centroid distance error. This metric measures the perpendicular distance from each vertebral centroid to the fitted line. An elevated centroid distance error indicates a deviation from normal spinal alignment, with larger errors signifying greater vertebral displacement and, consequently, a higher likelihood of spondylolisthesis.

Our proposed approach offers several advantages over traditional diagnostic approaches. First, by automating the vertebral detection and measurement process, it eliminates the subjectivity and variability introduced by manual methods. Second, the use of deep learning allows for rapid and scalable analysis, which is particularly valuable in clinical settings where large volumes of imaging data need to be processed quickly and accurately. Lastly, the centroid distance error provides a quantifiable measure of vertebral displacement, allowing clinicians to objectively assess the severity of spondylolisthesis and monitor its progression over time.

In summary, the proposed method aims to provide a reliable, efficient, and automated solution for spondylolisthesis detection. By leveraging state-of-the-art deep learning models like SSD, combined with robust centroid analysis, this approach holds the potential to significantly improve the diagnostic workflow in spinal healthcare, reducing both the time required for analysis and the risk of diagnostic errors.

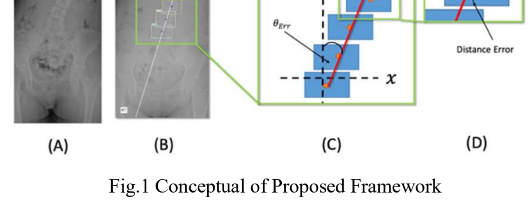

Fig.1 Conceptual of Proposed Framework

The objective of this research is to improve accuracy and reduce computational time in spondylolisthesis identification. Our proposed method provides an efficient and automate, Spondylolisthesis detection that can help in preliminary medical analysis.

II. Background

Spondylolisthesis is a condition where one vertebra slips forward over the adjacent vertebra, leading to various degrees of spinal instability. This condition primarily affects the lumbar spine and can result in significant pain, neurological deficits, and diminished quality of life [1]. The early detection and accurate assessment of spondylolisthesis are crucial for effective management and treatment strategies, which may range from conservative approaches to surgical interventions [2].

A. Pathophysiology of Spondylolisthesis

Spondylolisthesis can result from multiple factors, including degenerative changes, traumatic injuries, congenital anomalies, or pathological conditions [4]. It is classified into several grades based on the degree of slip, with Grade I indicating a minimal shift and Grade IV representing near-total slippage. The pathophysiological implications of spondylolisthesis can lead to nerve root compression, spinal stenosis, and altered biomechanics of the spine, necessitating timely intervention as shown in Fig. 2.

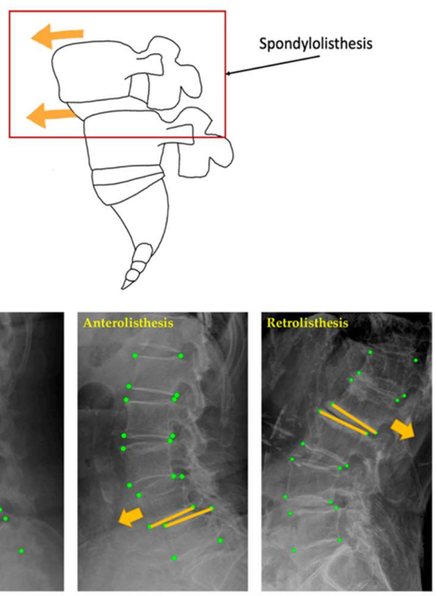

Fig.2 Pathophysiology of Spondylolisthesis

In Fig. 2, in X-ray imaging, spondylolisthesis can be visualized as a misalignment in the vertebrae. Radiological examination is typically the first-line diagnostic tool used to confirm the presence of this condition, with lateral (side view) and anteroposterior (front-to-back view) X-rays being the most common views taken.

B. Traditional Diagnostic Approaches

Normally, the diagnosis of spondylolisthesis relies on radiological assessments. X-rays are often the first imaging modality employed to visualize vertebral alignment [1]. However, the interpretation of these images is subjective and can vary significantly between practitioners. Advanced imaging techniques, such as MRI and CT scans, provide better anatomical detail and allow for the assessment of soft tissue structures; however, these methods are more expensive and less accessible [5].

III. Proposed Method

This section outlines the proposed methodology for the automated identification of spondylolisthesis in the lumbar spine. Fig. 3 demonstrates the approach leverages state-of-the-art deep learning techniques, specifically the SSD architecture, for the detection of lumbar vertebrae. Subsequently, we calculate the centroids of these vertebrae and assess their alignment using centroid distance error as a diagnostic metric. The methodology is structured into the following key components: dataset preparation, lumbar vertebrae detection using SSD, centroid calculation, linear fitting of centroids, and distance error calculation.

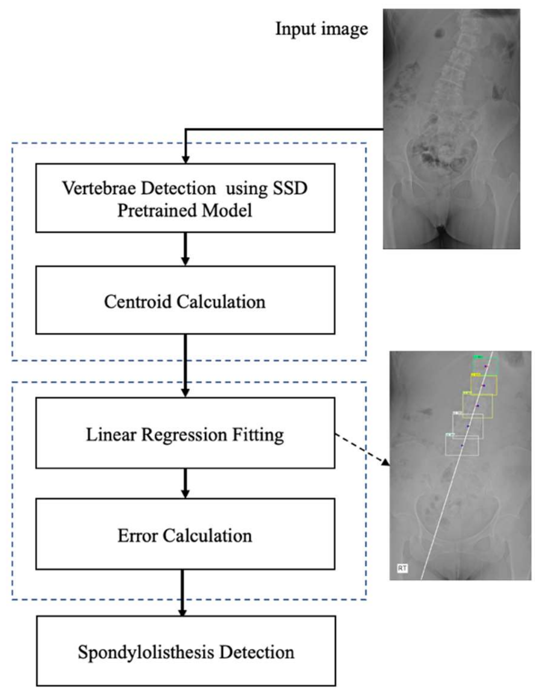

Fig.3 Proposed Method

A. Dataset

For this study, we utilize a dataset comprising labeled medical images of the lumbar spine, which include X-rays images. Klinwichit et. al. [6] introduced an Open Dataset contains Lumbar X-Ray images with Spondylolisthesis cases entitled “BUU-LSPINE”. The dataset consists of plain film images from 3,600 patients, annotated with vertebral positions, spondylolisthesis diagnoses, and ground truth labels for lumbosacral transitional vertebrae (LSTV). The dataset is then split into to 80 percent training set (2,880 images) and 20 percent testing set (720 images) to avoid overfit problem.

B. Lumbar Vertebrae Detection Using SSD

Using the Single Shot MultiBox Detector (SSD300) from PyTorch for lumbar vertebrae detection in X-ray images involves training the model to locate and classify the lumbar vertebrae (L1 to L5) by predicting bounding boxes around each vertebra. The SSD300 model processes the entire X-ray image in a single pass, leveraging convolutional feature maps to detect vertebrae at various scales, ensuring accuracy across different vertebra sizes. By minimizing localization and confidence losses during training, SSD300 efficiently learns to differentiate between lumbar vertebrae and background structures. Once trained, SSD300 can rapidly detect and classify vertebrae in new images. Once the dataset is prepared, the SSD model is trained to detect vertebrae. SSD employs a unified neural network architecture that directly predicts bounding boxes and class probabilities from full images in a single pass. The architecture comprises multiple convolutional layers followed by regression layers, which produce both the bounding box coordinates and the associated confidence scores. During training, the model is optimized using an annotated dataset, with the loss function typically combining object detection and localization components to minimize errors in vertebra localization and classification. A validation set is incorporated to evaluate performance and mitigate overfitting. Following training, the model is deployed for inference on previously unseen medical images, where it outputs bounding boxes around detected vertebrae along with confidence scores. A confidence threshold is applied to exclude detections with low confidence, ensuring robust identification of vertebral structures. The parameter set is shown in Table I.

TABLE I. PARAMETER SETUP

Parameter	Value/Range
Model Architecture	SSD
Batch Size	16
Learning Rate	0.001
Optimizer	Adam
Epochs	100
Confidence Threshold	0.7
IoU Threshold	0.45
Validation Dataset	10-fold cross validation
Loss Function	Cross-Entropy + IoU Loss
Non-Max Suppression	Enabled (NMS threshold: 0.45)
GPU Usage	NVIDIA GPUs with CUDA support RTX 3080
Evaluation Metrics	Precision, Recall, F1-score

The result from the localization is presented in the bounding box for each vertebrae. In Fig. 4, the vertebrae of lumbar spine are located.

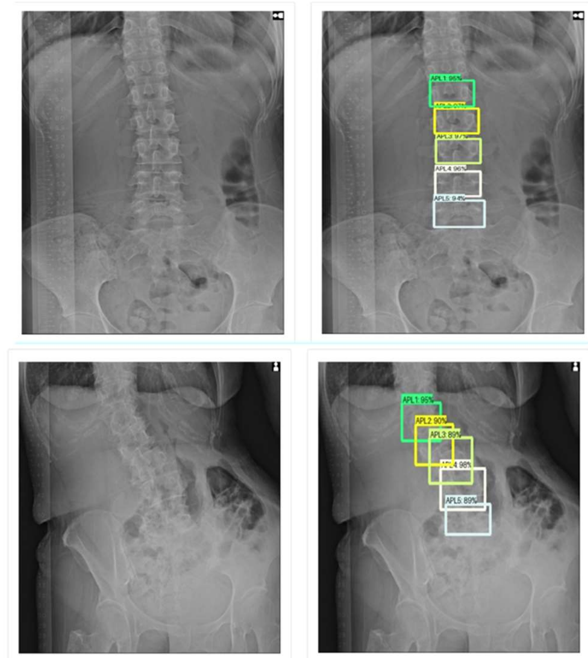

Fig.4 Bounding box of each Lumbar Vertebrae

C. Centroid Calculation

After the lumbar vertebrae have been detected, we calculate the centroid for each vertebra. Bounding Box Analysis: For each detected bounding box, the centroid is computed using the coordinates of the bounding box corners. The centroid (x_c, y_c) of a bounding box defined by $(x_{min}, y_{min}, x_{max}, y_{max})$ can be calculated using the Eq. (1).

$$x_c = \frac{x_{min} + x_{max}}{2}, y_c = \frac{y_{min} + y_{max}}{2} \quad (1)$$

Centroid Collection: Store the centroids of all detected vertebrae for further analysis. This data will serve as the basis for assessing vertebral alignment.

D. Linear Fitting of Centroids

To evaluate the alignment of the lumbar vertebrae, a linear regression line is fitted through the calculated centroid. The centroids are subjected to linear regression analysis to determine the best-fit line that represents the ideal alignment of vertebrae in a healthy spine. The linear equation can be expressed in the form of Eq. (2).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \varepsilon \quad (2)$$

Where m is the slope and b is the y-intercept. In Fig. 5, the fitted line is visualized alongside the centroids on a graph, providing a clear representation of vertebral alignment.

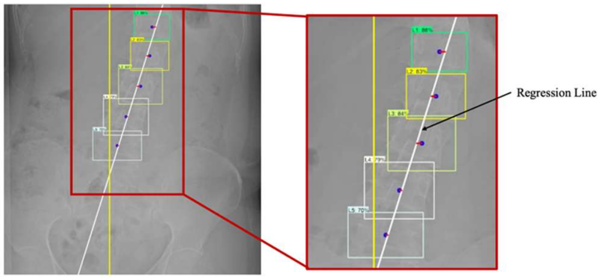

Fig.5 Regression Line from Vertebra centroid

E. Distance Error Calculation

The final step involves quantifying the alignment of each vertebra relative to the fitted line by calculating the centroid distance error. For each centroid, the perpendicular distance d_i rom the centroid (x_c, y_c) o the linear line can be calculated using the Eq. (3) derived from the point-to-line distance.

$$d_i = \frac{\left|Ax_{c_i} + By_{c_i} + C\right|}{\sqrt{A^2 + B^2}} \quad (3)$$

where A, B, and C are coefficients derived from the linear equation of the fitted line. Algorithm I show the process in determination of spondylolisthesis detection

Algorithm I. Spondylolisthesis detection

```
Algorithm: Spondylolisthesis Detection
    Input: Centroid C_n of vertebrae from Localization Process
INITIALIZE list of centroid C_n
FOR EACH vertebra centroid in the image
    ALIGN adjacency centroid C_i
END FOR
COMPUTE regression line L = β_0 + β_1C_1 + β_2C_2 + ⋯ + β_nC_n
IF ~(L ⊥ X_axis):
    Mark vertebra as Spondylolisthesis
ELSE:
    FOR EACH centroid C_i
        COMPUTE error E_i between C_i and L
    END FOR
    COMPUTE Thresh_reg using Standard Deviation σ^2 of E_n
    IF E_i > Thresh_reg:
        Mark vertebra as Spondylolisthesis
    ELSE
        Mark vertebra as Normal
    END IF
END IF
   Output: Detection results for each vertebra
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The calculated distances provide a quantitative measure of vertebral misalignment. Larger distances indicate a greater degree of displacement, which may suggest the presence of spondylolisthesis as illustrated in Fig. 6.

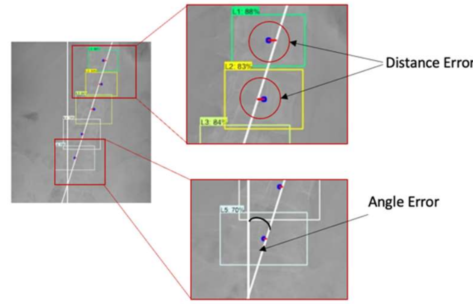

Fig. 6 Distance Error and Angle Error

In Fig. 7, the error from the regression line is demonstrated. If the error is between the red line, the vertebrae is determined as Normal. On the other hand, the data with an error above and below the red line is decided as Abnormal or Spondylolisthesis.

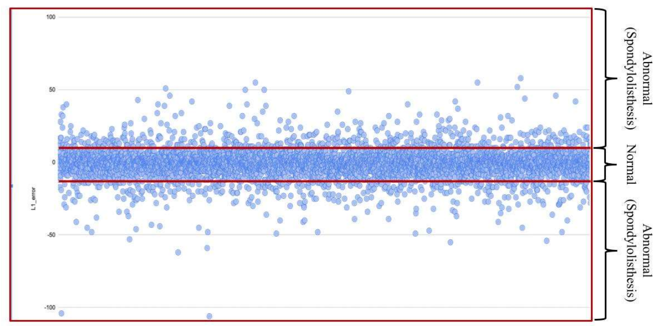

Fig.7 Scatter plot of error value from the regression and centroid of each vertebrae.

IV. Result and Discussion

In this section, we present the results of the proposed method for identifying spondylolisthesis in the lumbar spine was evaluated. The proposed approach demonstrated impressive detection capabilities, achieving a precision of 0.88, recall of 0.89, F1 score of 0.85. This performance indicates a high level of accuracy in identifying Spondylolisthesis, this approach established a threshold for diagnosing, demonstrating an accuracy. The advantages of the proposed automated framework in terms of efficiency, consistency, and scalability.

In addition, the results illustrate the potential of the automated method to enhance clinical diagnostics. By providing an objective measure of vertebral alignment, the centroid distance error facilitates more accurate diagnoses and timely interventions, addressing the limitations of subjective manual assessments. Furthermore, the proposed method can be seamlessly integrated into clinical workflows, allowing for rapid analysis of large datasets. The following table summarizes the performance metrics of the proposed method applying in various dataset.

TABLE II. PERFORMANCE EVALUATION

Metric	Dataset		
	Klinwichit et. al. [6]	Cai et. al. [7]	Fraiwan et. al. [8]
Precision	0.88	0.81	0.79
Recall	0.89	0.83	0.77
F1-Score	0.85	0.86	0.78

Table II emphasizes the performance of the proposed approach in detecting Spondylolisthesis, demonstrating that the proposed method significantly reduces diagnostic errors and enhances efficiency in identifying spondylolisthesis. While the results are promising, it is important to note the limitations of the study, including the dataset size and generalizability to other spinal disorders. Future research should focus on refining the model further and exploring its application across diverse patient populations and imaging modalities to validate its clinical effectiveness.

V. CONCLUSION AND FUTURE WORK

This study presents an innovative automated method for identifying spondylolisthesis in the lumbar spine, leveraging deep learning techniques with the SSD architecture for precise lumbar vertebrae detection and centroid distance error for assessing vertebral alignment. The results demonstrate that our method significantly enhances diagnostic accuracy and efficiency compared to traditional manual inspection techniques, achieving a high Precision and consistent identification of vertebral centroids. By establishing a robust framework for measuring centroid distance errors, we can objectively quantify misalignments indicative of spondylolisthesis, facilitating timely and accurate diagnoses that are essential for effective patient management.

Despite the promising outcomes, this research acknowledges several limitations, including the dependency on the dataset's size and diversity, as well as potential challenges in generalizing the model to other spinal conditions. Future work will focus on several key areas to further improve and validate the proposed method. First, we aim to expand the dataset by incorporating a broader range of imaging modalities and patient demographics, which will enhance the model's robustness and applicability in diverse clinical settings. Additionally, exploring advanced techniques such as transfer learning and ensemble methods could improve the model's performance and accuracy further.

Moreover, future research will investigate the integration of clinical parameters, such as patient history and physical examination findings, to enhance the predictive capabilities of the model. This multi-faceted approach may lead to the development of a comprehensive diagnostic tool that combines automated image analysis with clinical insights. Lastly, we intend to conduct clinical trials to evaluate the method's effectiveness in real-world settings, which will provide valuable feedback for refining the algorithm and its clinical implementation.

VI. ACKNOWLEDGEMENT

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