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A Deep Learning Based Approach for Detection of Lumbar Spondylolisthesis from X-Ray Images

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ABSTRACT: The term lumbar spondylolisthesis is utilized to pinpoint the displacement of a vertebra within the lower spinal area, when it moves forward out of its normal position. Such being displaced can result into the nerve pine irritation and hence, the symptoms such as lower back and leg pain will emerge. While the research shows that adults are more likely to get the condition than children, the specific age in which some people develop it and others do not is not clear. Reports say that there's 6-7% incidence of isthmic spondylolisthesis among persons aged 18 by now. In this figure which rises to 18% for adults and usually affects ladies aged above 60. The occurrence of spondylolisthesis seems to uncover some sex related aspects which show through as isthmic becomes more prevalent in males and dynamics becomes commoner in females. In the course of our research, Lumbar-Net a deep learning net that has the ability of automatic identification of the lumbar spondylolisthesis in the images of an X-ray is our focus. Lumbar-Net computes a P-assessment in that situation and this implies the difference of the ramification of left and right vertebrae. A CG-rate that is greater than a certain threshold (e.g., 20%) implies the presence of an abnormality. P-Grading is not a category representing severity however it does signify potential more severe technological and linguistic slide.

KEYWORDS: LUMBAR SPONDYLOLISTHESIS, P-GRADE, SPINE, X-RAY IMAGE, LUMBAR-NET

I. INTRODUCTION

Spondylolisthesis involves the movement of a vertebral body in relation to the vertebra immediately below it [4-6]. Anterolisthesis and retrolisthesis refer to forward and backward shifts concerning the underlying vertebra [6, 7]. Lumbar spondylolysis constitutes roughly 50%-81% of all spondylolisthesis cases [4]. The condition can arise from genetic factors, disc degeneration, or repeated lumbar hyperflexion combined with significant rotational stress.

The Meyerding classification, consisting of five variations, is commonly employed in both clinical settings and research because of its straightforwardness and user-friendliness [7,11]. The extent of slippage is determined by the displacement of the superior vertebra in relation to the inferior

Table 1 shows the correlation between P-grade and the degree of vertebral slippage. P-grades below or above 50% indicate mild or severe slippage. A P-grade greater than 100% indicates total spinal slippage, the most severe form of the illness [12].

Table 1

P-Grade	%Slip	Description
Grade-I	0-25%	Low Grade
Grade-II	26-50%	
Grade-III	51-75%	High Grade
Grade-IV	76-100%	Very high Grade
Grade-V	>100%	Spondylolisthesis

Along with many other stages, a deep learning network for segmenting the images of the lumbar region presents a few critical sequencies. The dataset is preliminarily created by compiling X-ray images of lumbar spine and then passing the data through preprocessing module in order to obtain better quality data and one format. In fact, those preprocessed X-ray images are what used for training the deep-learning network consisting of the networks like the convolutional

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neural networks (CNNs) or more advance architectures. The network performs feature and pattern analysis for feature differentiation and partitioning during the training phase, and which involves lumber localization from the remaining part of the images. The first deformation of the operation is classification of each pixel situated in the image as a part of the lumbar area or not. When the deep learning network is finally trained, it can be effective in identifying the lumbar region in the X-Ray images that are coming later on and consequently facilitating the medical diagnosis and treatment planning for Spondylolisthesis.

II. RELATED WORK

[1] The YOLOv3 model presented by Fatih Varçın, Hasan Erbay, Eyüp Çetin, İhsan Çetin, and Turgut Kültür has been utilized extensively and widely recognized as a reliable solution. While it has some potential issues, medical image analysis is one application that must be taken into account as it attempts implementation of these technologies. The model may be failing occasionally to spot the small objects, the closely clustered objects or the very tiny objects in the images, there can be a problem with the loss of contextualization as each complete image is processed simultaneously, there is dependence of current model on the best quality of training data for the peak performance, the black-box model does not interpret well, it is the brain sucker of the model that requires expertise for fine tuning.

The CoLumbo platform developed by SmartSoft Ltd.[2] in Varna, Bulgaria, is a state-of-art software that offers a solution to the diagnosing of lumbar (lower back) spine degenerative changes by autonomy. This architecture is a neural network based on convolutional layer that has been designed to reach our goals. Ultimately, the objective of the CoLumbo platform is to detect certain pathologies in multi-modality and 3D MR images, specifically disc hernia, disc bulge, nerve root compression, spinal canal stenosis and spondylolisthesis. Implementing a deep learning algorithm together with CNN was shown to be an efficient and precise system in medical image analysis using the CoLumbo system, which was demonstrated. The connection between CNN (CoLumbo) and the segmentation design of the U-Net which utilizes lower-resolution classification features to provide a context and higher-resolution feature to depict details for better precision is outlined in this statement. One of the weaknesses of is its retrospective nature, due to which validity of clinical data is decrease which is also stated in my previous sentence that sample size is relatively smaller than the required addressing and it has certain exclusion criteria which not depict the true clinical scenario of most aging societies. Co Lumbo had the lowest PPVs of 13.11% to 75.00%, which remained fairly low despite excluding the findings of physicians at the time considered clinically non-relevant. Such realization is certainly capable of preventing the intended system from being effectively replaceable as overall radiologists fatigue remains a key issue. It highlights the significance of ongoing studies to evaluate whether the interface is able to do well in the standardization of results, decrease the amount of time needed for reading, and boost interobserver agreement. It reveals the need of continuous validation and modification of the CoLumbo system prior being widely receipted by the clinical use.

The classifier[3] Alex-Net, designed specifically for image classification tasks can be used to assess imaging data gathered for spondylolisthesis. The spinal radiographic images could go into the network's input layer as 2D or 3D images. The images may be of different views or modalities used in lumbar spine imaging. Hence, Alex-Net would then pass through the convolutional layers, focus on defining the vertebral misalignment, disc degeneration, or spinal canal stenosis among others. By using ReLU activations the model will become non-linear and therefore easily capture the most complex patterns and max-pooling layers will give the opportunity to round up the feature maps so to keep the vital information unharmed. The last fully connected layers would scrutinize the extracted features and then make judgments or classifications which concern spondylolisthesis severity or progression depending on current data from imaging. As a result, the complex features which can be readily captured by the up-to-date networks may remain unclear and unsuitable for the AlexNet network with its small network capacity. The fixed number of pixels in AlexNet, specifically the input pixel, determines that the network performance could be significantly affected though changing the imaging resolution or changing the size of the image in width and height.

III. PROPOSED ALGORITHM

LUMBAR-NET SEGMENTATION

The usual segmentation of the lumbar area in various medical images is manual or rule-based and is composed of many steps. This method is based on the introduction of the custom functionality such as edging detecting, thresholding, and morphological operations aiming to single out the lumbar location in X-ray images. The realization of their usefulness, methods discussed here are always confronted with problems of anatomy complexity, images quality noise and weak contrast.

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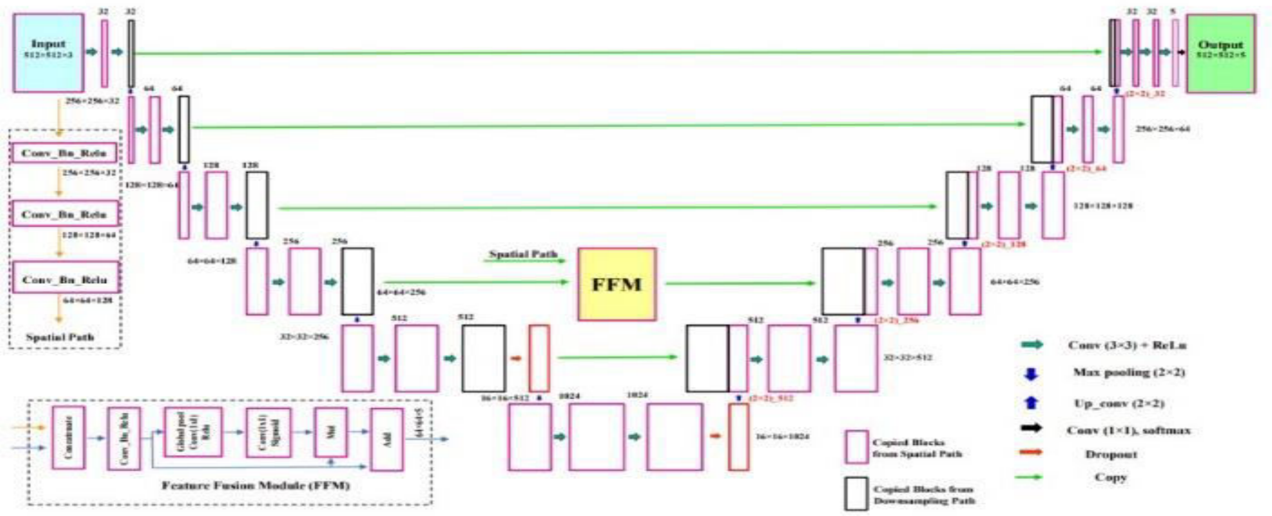
Lumbar-Net outperforms previous approaches of lumbar area segmentation in medical imaging. It is a deep learning architecture can automatically learn and extract complex features from X-Ray images, reducing the need for manual feature engineering and increasing accuracy.

Lumbar-Net can be thought of as a modified or customized version of the U-Net architecture designed exclusively for lumbar region segmentation in medical images. Lumbar-Net, like U-Net, uses an encoder-decoder structure with skip links to capture both high-level contextual information and fine-grained minutiae required for successful segmentation. However, Lumbar-Net includes significant architectural advancements and modification to solve the special issues given by lumbar spine X-Ray pictures.

The input of the Lumbar-Net architecture is clearly visible at the top of Fig 1 and consists of a 512×512×3 lumbar vertebrae X-ray. Lumbar-Net is structured with two primary pathways: resolve and go deeper into detail. Navigating through the threads of an image can be described as an example of the spatial pathway. The deep layers featuring batch normalization (BN) and rectified linear unit (ReLU) activation functions are then used to extract only spatially related data. When we get the layers of convolutional techniques like batch normalization and ReLU activation simultaneously trying to figure out the context and cleaning the data by down-sampling, they get entangled into pooling techniques. Batch normalization and the Rectified Linear Unit (ReLU) activation function are crucial for improving the network's

Fig 1 Lumbar-Net Architecture



performance and training stability. Batch normalization aids in the normalization of input to a layer over a batch of samples, decreasing internal covariate shift and increasing convergence while training. This normalization ensures that the network learns more resilient features and improves optimization efficiency by minimizing vanishing or exploding gradients. In contrast, the ReLU activation function provides non-linearity throughout the network, allowing it to effectively model complicated relationships and learn representations. ReLU converts negative values to zero while leaving positive values unmodified, so addressing the vanishing gradient problem and boosting sparsity in activations, making the network more expressive and less difficult to train.

To preserve the same number of channels in the encoder and decoder, skip connections are added between blocks in the down sampling and up sampling paths.

The two pathways then meet in a feature fusion module (FFM), where the information is integrated. The Feature Fission Module in Lumbar-Net is critical in improving the network's ability to gather fine-grained features and spatial information required for effective lumbar area segmentation in medical imagery. This module splits the encoder's feature maps into many branches, each focusing on a distinct element or scale of the input data. The Feature Fission

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Module often uses processes like max pooling to extract features at different sizes and resolutions. This max pooling processing power allows Lumbar-Net to tolerate variances in lumbar anatomy, patient location, and picture quality, resulting in better segmentation performance and robustness.

A sigmoid-activated 1x1 convolution in a five dimensional space is what the last layer does to produce the `probability map' which is same-sized with the input (512 x 512).

P-Grade calculation

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.

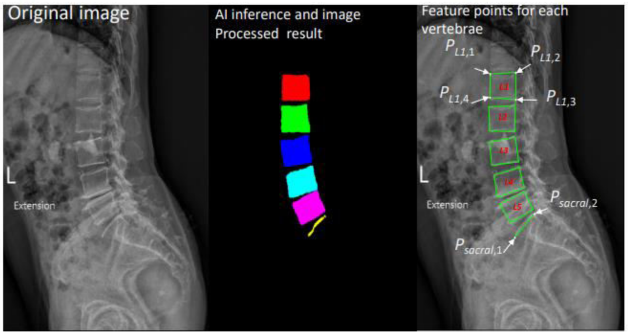

Fig 2: This visual is of the original on the left and the middle one with color shifts that differ the vertebrae of L1 from S1. On the right, you observe the details of feature points for each vertebra and the sacrum being computed.

The four points of each vertebra are arranged in a counterclockwise direction beginning at the upper left. Fig 2 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 shown in the equations below:
where f_{pgrade} represents the shift value of the lower plate of the i-th lumbar vertebra relative to the upper plate of the jth lumbar vertebra.

$$f_{pgrade}(m,n) = p_{grade}(i,j) > K1, \tag{2}$$

$$p_{grade}(i,j) = \frac{D(P_{i,proj}, P_{j,2})}{\sqrt{\|P_{j,1} - P_{j,2}\|^2}}, \tag{3}$$

$$D(P_{i,proj}, P_{j,2}) = \sqrt{\|P_{i,proj} - p_{j,2}\|^2} \tag{4}$$

The indexes i and j correspond to the proximal vertebral regions i ∈(L1, L2, L3, L4, L5) and j ∈ $(L2, L3, L4, L5, S1)$. 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.

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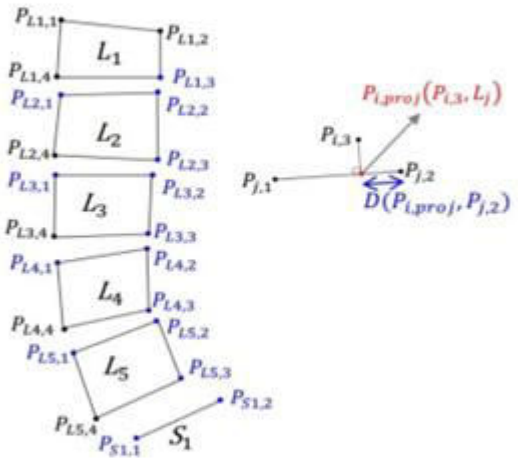

Fig 3: The lumbar spine comprises five vertebrae, each marked by four points, while the sacrum has two points. The projected point can fall either within or outside the segmented line.

Additionally, f_{pgrade} is calculated by dividing $D(P_{i,proj}, P_{j,2})$ by the upper-plate length of the j-th lumbar vertebra, as shown in Figure 3. The projected point is either within or beyond the segmented line indicating the top plate of the j-th lumbar vertebra.

IV. PSEUDO CODE

```
Step 1:  Start
Step 2:  Check the following condition to calculate the grade.
             if slip percent is greater than 75%
                    then grade 4
             else if slip percent greater than 50 %
                    then grade 3
             else if slip percent greater than 25%
                    then grade 2
             else
                    grade 1
Step 3:  Initialize the grade index value to -1.
Step 4:  Perform the following steps to update the grade index according to the slip percent.
             if(percent > 75):
                    grade_idx = 3
            else if(percent > 50):
                    grade_idx = 2
            else if(percent > 25):
                    grade_idx = 1
            else
                     grade_idx = 0
Step 5: End
```

V. SIMULATION RESULTS

The Lumbar-Net architecture has various advantages in the field of neural networks. For starters, its hierarchical structure promotes efficient information flow by grouping neurons into layers, allowing for parallel processing and faster computations. This architecture also improves model interpretability by describing complicated features in a more understandable way through data abstraction across numerous layers. Moreover, the modular design of Lumbar-Net facilitates straightforward scalability and customization, rendering it suitable for a diverse range of tasks and datasets. Its capacity to acquire hierarchical data representations is particularly advantageous for tasks involving spatial or temporal interdependence, such as image recognition or time series analysis.

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Along with the advantages of the deep learning method, the limitations should be taken into account as well. Orthopedists not only got X-ray images, but also performed separate evaluation of spondylolisthesis without considering interobserver and intra bserver variabilities. The method has become ineffective in determining the subject matter or the extent of spondylolisthesis. Notwithstanding, the intricate Bony structure with its interposed and crawling elements poses difficulty, particularly in X-ray of people.

Osteoporosis can introduce extra degeneration into segmentative image processes.

In Identifying the fifth lumbar vertebra (L5) and first sacrum (S1) might be challenging due to their proximity to the pelvis or the presence of lumbar sacralization, a variant of L5 and S1 as shown in fig 4.

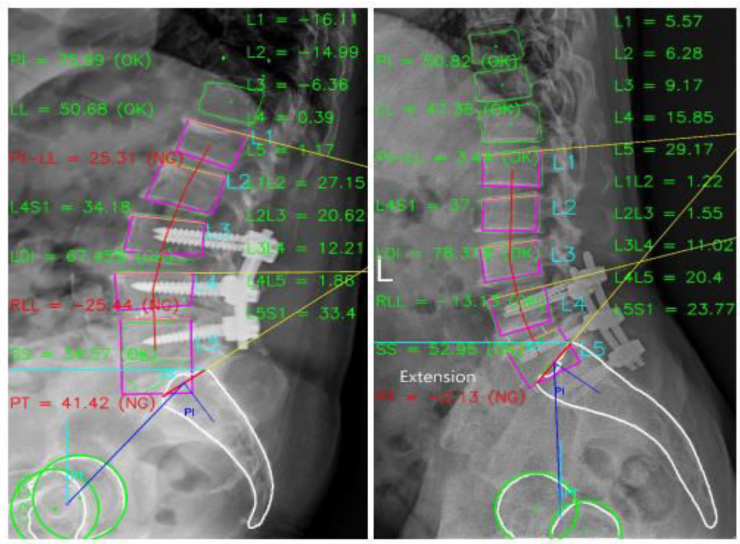

Fig 4 : Superimposition between the L5 and S1

Vertebral osteophytes (bone spurs) can cause mistakes in quadrilateral fitting as they do not accurately reflect vertebral corner as shown in fig 5. If the corners cannot be accurately spotted, all assessments will fail. Identifying lesions in X-ray pictures of patients with co-existing osteoporosis, degenerative spine disease, or lumbar sacralization can be problematic.

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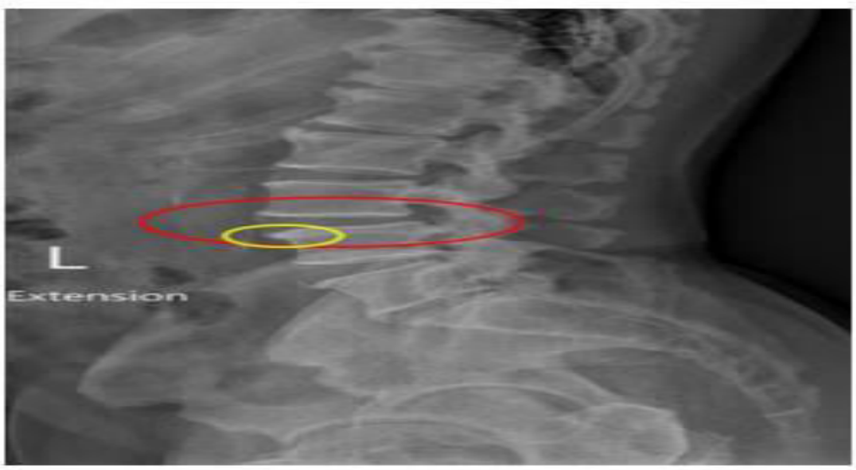

Fig 5: Vertebral Spurs

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Despite these factors affecting the model's performance, the overall results are worth considering (see Fig 6). This model has the ability to detect spondylolisthesis from readily available X-ray images in areas with limited resources and healthcare providers.

Fig 6a : No Spondylolisthesis

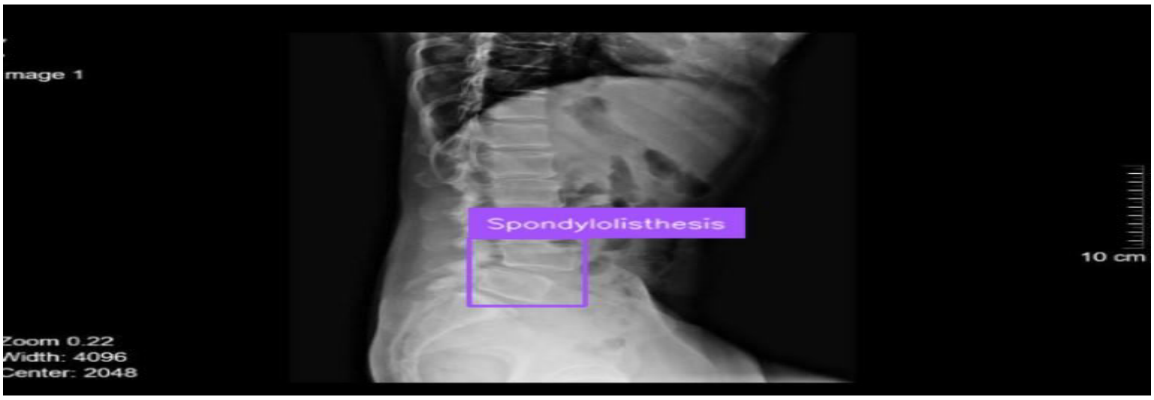

Fig 6 b:Spondylolisthesis at L4-L5

The Lumbar Net model responded aptly to real-life spinal images test. A model that already has undergone intensive training and validation was found to have a great deal of accuracy and reliability in terms of detecting spondylolisthesis and other spinal pathologies. The mean accurate precision was found to be 98.2% as shown in the Fig 7.

Fig 7: Mean Accurate Precision of Lumbar-Net

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VI. CONCLUSION AND FUTURE WORK

The paradigm represented by the Lumbar-Net is a novel make of a neural network, presenting the difficulty of complexity increase, data processing limitations, problematic interpretability and the hindering problems associated with the overfitting and the gradient vanishing. Developing a multilevel complex structure introduces view of details and associations; however it implies high level of professional expertise for specific hardware and software configurations.

The P-grade served in the ROI definition, and the endpoint was a decrease in lumbar vertebrae slippage that will be assessed through P-grade values. This approach was successful for the spinal tract dissection and could be used in the healthcare system to identify many spinal illnesses.

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