iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IV **Month of publication:** April 2025

DOI: https://doi.org/10.22214/ijraset.2025.68692

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Deep Learning Based Image Segmentation for Diagnosis of Spondylolis thesis from Lumbar Spine X-RAY

D.Mahita[1], A.Sravya[2], Ch.Shireesha[3], M.Jhansi[4], Dr.P.M.K.Prasad[5]
[1 2, 3, 4]*UGScholar,Dept.of ECE,Gayatri vidya parishad college of engineering for women Kommadi , Andhra Pradesh ,India*
[5]*Professor and Head of the Department of ECE*

***Abstract:** Spondylolisthesis is a condition of Spine which occurs due to slippage of vertebrae. which can causepain and resultsin limited mobility and nerve compression. Accurate detection in early stages important for prevention of further complications. Traditional methos heavily depends on human examination of X-ray images, which can cause manual errors. To improve the detection of spondylolisthesis in X-ray images we used deep learning techniques. YOLO (you only look once) is known for itsreal time processing capability and high precision, works faster, detects and segments in one step based on percentage of vertebral slippage, and gives more accurate results. We compared the results obtained by YOLOV8 and YOLOV11. This study supports the use of deep learning techniques to assist medical professionals in making more accurate assessments.*
***Keywords:** Spondylolisthesis,Segmentation,Augmentation,MeyerdingClassification,YOLOv8,YOLOv11*

I. INTRODUCTION

Spondylolisthesis mainly occurs in lower back that is lumber spine it may also occur in thoratic spine and cervical spine but is very rare. This condition arises from a variety of causes, including degenerative changes, congenital defects, traumatic injuries, and pathological processes, with its severity classified using the Meyerding grading system. While mild cases (Grade I: 1%–25% slippage) may remain asymptomatic, higher grades (Grade II–V) often manifest as lower back pain, sciatica, muscle stiffness, and neurological deficits due to nerve compression. Accurate and timely diagnosis is critical for effective treatment planning, yet traditional diagnostic methodsheavily rely on manual interpretation of medical imaging—such as X-rays, MRI, CT scans, and bone scintigraphy—which can be time-consuming and subject tohuman error. The advent of artificial intelligence (AI) and deep learning technologies offers a transformative opportunity to enhance the diagnostic process for spondylolisthesis. Convolutional Neural Networks (CNNs), particularly when integrated with advanced object detection frameworks like You Only Look Once (YOLO), have demonstrated remarkable potential in medical image analysis. These tools enable automated detection, localization, and classification of anatomical structures, significantly reducing diagnostic time while improving consistency and precision. Despite these advancements, the application of YOLO-based image segmentation to lumbar spine X-ray images for spondylolisthesis detection remains underexplored, presenting a compelling avenue for research and innovation. This study introduces an AI-driven approach to detect and classify spondylolisthesis from lumbar spine X-ray images using YOLO-based segmentation. The primary objective is to develop a system capable of analysing vertebral alignment, identifying slippage, and grading its severity in an automated manner. By leveraging deep learning, this project aims to streamline the diagnostic workflow, offering a faster, more reliable tool for clinicians to assess spondylolisthesis and plan interventions. The following sections outline the methodology, implementation,andevaluationofthisnovelsystem,withthepotentialtorevolutionizespinaldiagnosticsandimprove patient outcomes.

II. LITERATURESURVEY

In [1The research paper titled "Using Deep Transfer Learning to Detect Scoliosis and Spondylolisthesis from X-ray Images" by Mohammad Fraiwan, Ziad Audat, Luay Fraiwan, and Tarek Manasreh (2022) explores a deep learning-based solution for detecting spinal disorders, specifically scoliosis and spondylolisthesis, directly from X-ray images. The study aims to eliminate the need for manual measurements, which are time-consuming and error-prone, by utilizing automated classification through deep transfer learning. A dataset of 338 labeled X-ray images collected from King Abdullah University Hospital was used, including 188 scoliosis, 79 spondylolisthesis, and 71 healthy cases. The images underwent preprocessing such as grayscale-to-RGB conversion, resizing, and data augmentation techniques like random flips and pixel translation to enhance model robustness.

Fourteen different pre-trained CNN architectures including DenseNet-201, ResNet-101, ResNet-50, Inception-v3, and MobileNet-v2 were fine-tuned for binary and multi-class classification by replacing their final layers. The models were trained using MATLAB R2021a,employing a powerful hardware setup and optimized using Stochastic Gradient Descent with Momentum (SGDM) over six epochs. DenseNet-201 delivered the highest three-class classification accuracy of 96.73%, while binary classification results exceeded 98% accuracy in some models. Evaluation metrics included precision, recall, specificity, and F1-score. Despite impressive results, the studynotedseverallimitationssuchasarelativelysmallandpossiblyimbalanceddataset,lackofreal-worldclinicalvalidation, dependency on high-resolution images, and high computational demands. Moreover, theinterpretability of thedeep models remains a concern, as the "black box"nature limitsmedical professionals' trust. Still, the studyprovides promising insightsintousing AI for spinal diagnostics and suggests its potential for real-time clinical use with further validation and dataset expansion.

In [2], The paper "Automatic Lumbar Spondylolisthesis Measurement in CT Images" by Shu Liao and colleagues (2016), published in IEEE Transactions on Medical Imaging, presents an advanced method to automatically detect and quantify lumbar spondylolisthesis using CT scan data. Spondylolisthesis, the forward displacement of one vertebra over another, can cause chronic pain and mobility issues, and its diagnosis traditionally relies on manual evaluation by radiologists, which is subjective and time-consuming. The study aims to improve diagnostic precision and reduce variability through automation. The proposed methodology begins with preprocessing of CT images for noise removal and contrast enhancement to better highlight vertebral structures. Segmentationtechniques,includingbothtraditionaledgedetectionandpotentiallydeeplearning-basedU-Netmodels,areappliedto isolate vertebrae. Key anatomical features such as vertebral boundaries, endplates, and spinous processes are extracted to calculate slip percentages.Thesystem leveragesmachinelearning modelslikeSVMsand CNNs,trained on annotateddatasets,to classify the severity of spondylolisthesis. Validation against expert annotations using statistical measures like Mean Absolute Error (MAE) and Dice Similarity Coefficient (DSC) demonstrated the system's high accuracy and reliability. The method effectively reduces human error, improves efficiency, and supports clinical decision-making. However, the paper also highlights several limitations, including dependence on high-quality CT images, the need for large and well-annotated datasets, and lack of extensive clinical trials. The method's generalizability is also questioned due to variation in imaging protocols across institutions. Moreover, the computational cost and limited transparency of model decisions present challenges for practical implementation in diverse clinical environments. Despite these limitations, the work represents a significant step forward in applying AI for spinal diagnostics.

In [3], . The paper titled "SO-YOLO Based WBC Detection With Fourier Ptychographic Microscopy", authored by Xing Wang, Tingfa Xu, Jizhou Zhang, Sining Chen, and Yizhou Zhang (2018), introduces a cutting-edge method that merges deep learning with advanced microscopy to automate white blood cell (WBC) detection. The study integrates a modified object detection model called SO-YOLO (Self-Optimizing You Only Look Once) with Fourier Ptychographic Microscopy (FPM), a high-resolution imaging technique that offers detailed cellular visuals by computationally synthesizing images from multiple angles. This combinedapproach allows for accurate, real-time detection of WBCs in blood samples while maintaining high efficiency and low computational cost. During implementation, FPM was used to capture rich, high-resolution images of blood samples, followed by preprocessing techniques like normalization, noise reduction, and data augmentation to prepare the data. The SO-YOLO model was trained using a labeled dataset with bounding boxes and class labels for WBCs. It also utilized adaptive learning rate mechanisms and improved feature extraction to optimize accuracy. Performance was evaluated using key metrics such as precision, recall, F1- score, and mean average precision (mAP), showing superior results compared to traditional YOLO models, both in detection speed and classification performance. This method stands out for its potential application in automated hematology, especially in labs requiring fast and accurate analysis of blood samples. However, the study also presents several limitations. The requirement for specialized FPMequipmentmakesitlessaccessiblein standard laboratories,and thedeeplearning modelrequiresalargevolumeof annotated data and significant computational resources. Clinical validation is limited, and the black-box nature of AI models could hinder acceptance among medical professionals who require model explainability. Despite these challenges, the integration of SO- YOLO and FPM provides a promising foundation for future AI-driven diagnostic tools in pathology.

III. DATA SET COLLECTION

The BUU-LSPINE Dataset is a curated collection of lumbar spine X-ray images, created through a collaborative effort between Burapha University (BUU) inThailand and the KoreaInstitute of Oriental Medicine(KIOM) in South Korea. Itserves as a valuable resource for advancing research in medical image analysis, especially in the detection and evaluation of spinal disorders. Thedataset includes records from a total of 5,308 patients, though access is currently limited to a subset of 400 cases. Within this accessibleportion,thereareimagepairsfrom127 maleand273 femalepatients.Theagerangeofsubjectsspansfrom asyoung as6 years old to 89 years old, offering a broad demographic spectrum.

Each patient has X-ray scans taken from two standard clinical perspectives: the anteroposterior (AP) view and the lateral (LA) view. All images are provided in JPG format, facilitating compatibility with various image processing tools and deep learning frameworks. The diversity in age, gender, and imaging angles makes this dataset a robust foundation for training and evaluating machine learning models aimed at spinal diagnosis and assessment.

IV. METHODOLOGY

A. DataCollectionandPreparation

The BUU-LSPINE dataset is a curated resource tailored for lumbar spine X-ray image analysis, created through a collaborative initiativebetweenBuraphaUniversity(BUU),Thailand,andtheKoreaInstituteofOrientalMedicine(KIOM),SouthKorea.Designed to aid research in spinal disorder diagnosis, the dataset provides diverse radiographic samples of the lumbar region. While the full dataset comprises 5,308 patient records, only 400 were accessible for this study. Among these, there are 127 male and 273 female image pairs. The age distribution of the subjects ranges from 6 to 89 years. Each subject includes two standard radiographic views—anteroposterior (AP) and lateral (LA)—with all images provided in JPEG format, ensuring compatibility with standard image processing frameworks.

B. DataSplitting

Proper data partitioning is essential for robust model evaluation and performance generalization. The dataset was divided into three subsets: training, validation, and testing. A total of 800 images were used, with 640 allocated for training (80%), while 160images wereusedforvalidationandtesting(26and134respectively,comprising20%).Thisstratifiedsplitensuresthatthemodellearnsfrom a representative sample, tunes its hyperparameters efficiently, and is validated on previously unseen data, thus avoiding overfitting. Thefinaltestsetprovidesanunbiasedbenchmarkforthemodel'sreal-worldapplicability.

C. DataResizing

Tostandardizetheinputforneuralnetworkprocessing,allimageswereresizedtoaresolutionof640×640pixelsusingPython-based image manipulation tools. This uniformresizing ensures consistency across the dataset and optimizes model training.Image resizing is particularly critical for deep learning workflows, as it maintains spatial structure while allowing batch processing during training, ultimately enhancing computational efficiency and model accuracy.

D. CSVto YOLOFormat Conversion

Transforming annotation data from CSV to YOLO format is a crucial preprocessing step for training object detection models. In this project, imageannotationscontainingbounding boxcoordinatesand classlabelswereformatted toYOLO-compatibletextfiles.The YOLO segmentation format requires normalized polygon coordinates representing the object boundaries, expressed as: class_id x1 y1 x2 y2 x3 y3 x4 y4, with all values scaled to the range [0,1] relative to image dimensions. Separate conversions were conducted for lateral (LA) and anteroposterior (AP) images to ensure accurate training data generation for each X-ray view

$$x'_{center} = \frac{\left(\frac{x_1 + x_2}{2}\right)}{I_{width}}$$

x_1 and x_2 is coordinate of the first and second position on lumbar spine. I_{width} is the width of the image.

$$y'_{center} = \frac{\left(\frac{y_1 + y_2}{2}\right)}{I_{height}}$$

y_1 and y_2 is coordinate of the first and second position on lumbar spine. I_{height} is the height of the image.

Formulaeused

897.8728	504.3773	1171.021	601.7371	0
823.5008	684.2224	1080.422	803.2175	0
778.8776	778.8776	1053.378	826.2053	0
711.2667	985.767	1003.346	1046.617	0
692.3356	1065.548	992.5281	1072.309	0
667.9957	1280.551	966.8359	1295.425	0
674.7568	1400.898	965.4837	1340.048	0
715.3234	1609.14	1001.994	1534.767	0
746.4244	1703.795	1004.698	1571.277	0
831.6141	1902.571	1092.592	1764.645	0
889.7595	1989.113	1108.819	1816.029	0

Figure1CSVFormatLabels

```
0 0.404687 0.165625 0.528125 0.196875 0.487500 0.264062 0.371875 0.225000
1 0.351562 0.256250 0.475000 0.271875 0.453125 0.343750 0.320312 0.323437
2 0.312500 0.350000 0.448437 0.353125 0.435937 0.426563 0.301563 0.420312
3 0.304688 0.460938 0.435937 0.440625 0.451562 0.504687 0.321875 0.529687
4 0.335938 0.560937 0.453125 0.517188 0.493750 0.579688 0.375000 0.626563
5 0.401562 0.654687 0.500000 0.596875
```

Figure2YOLOFormatLabels

E. YOLOModelTraining

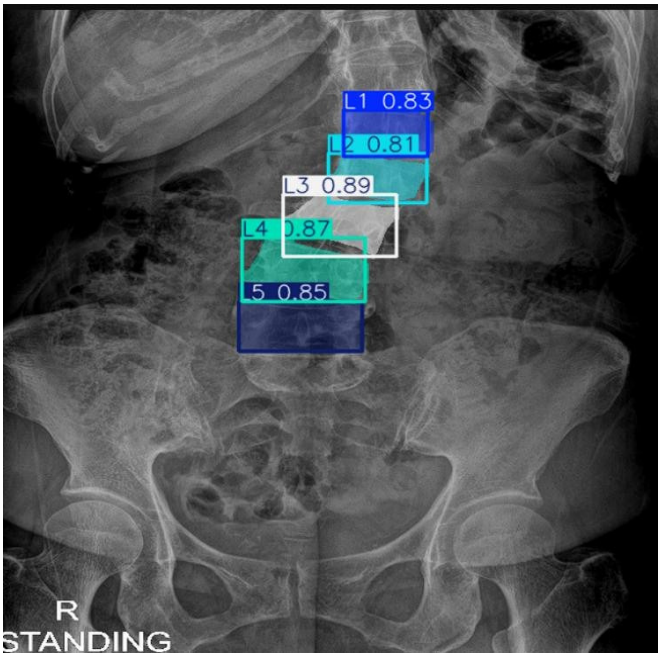
YOLO (You Only Look Once) is an advanced real-time object detection algorithm that simultaneously predicts object classes and bounding box coordinates in a single forward pass. This efficiency enables its application in time-sensitive fields like medical diagnostics. The training process began with the preparation of labeled images, which were pre-processed through resizing and augmentation. The model was initialized using pre- trained YOLOv8 weights and trained using a stochastic gradient descent optimizer.

Loss calculation involved three components: localization loss (bounding box accuracy), classification loss (label accuracy), and object loss (confidence of detection). Hyperparameters such as learning rate and batch size were tuned during training. Performance evaluation was conducted using validation metrics including precision, recall, and mean average precision (mAP). Once optimal results were achieved, the model was savedand prepared for deployment in real-time diagnostic applications.

F. Segmentation

Segmentation was performed to enhance diagnostic precision by detecting and isolating specific anatomical structures within the X-ray images. The input images were preprocessed and passed through the YOLOv8 segmentation model, which predicted class labels and generated pixel-level masks. Post-processing included applying non-maximum suppression (NMS) and mask refinement to ensure accuracy. The model's ability toproduce clear segmentation masks is particularly useful in medical applications, as it allows for detailed visualization of vertebral alignment and abnormalities.

The output masks highlighted the vertebral structures, thereby aiding in the diagnosis of spinal conditions such as spondylolisthesis. This mask-based segmentation offers more precise localization compared to traditional bounding boxes, significantly improving clinicaldecision-making.



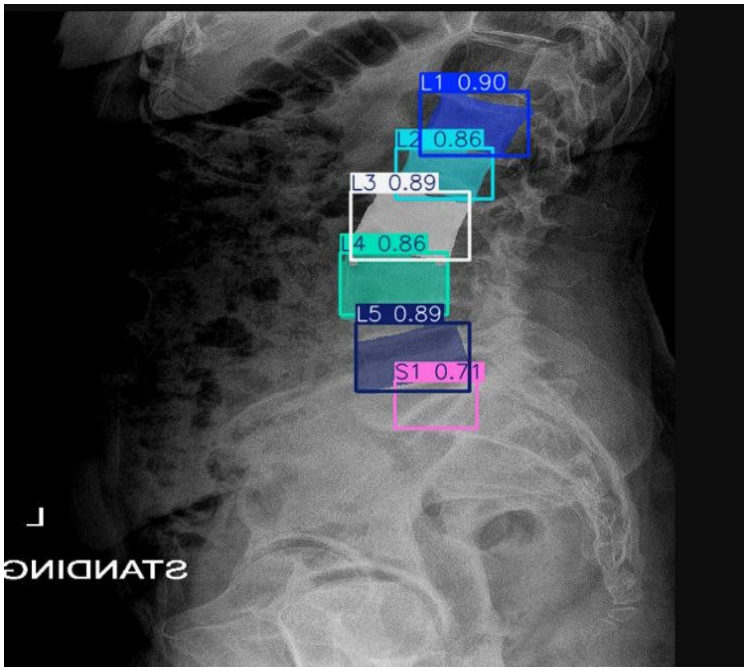


Figure3APviewimagewithbounding boxandsegmentedareaFigure 4 LAviewimagewithboundingbox andsegmentedarea

G. Data Augmentation

To improve the generalization capability and robustness of the YOLOv8 model in detecting and segmenting lumbar spine abnormalities, a range of data augmentation techniques were employed on the dataset. These augmentations were essential for mimicking the variations commonly encountered in real-world medical imaging scenarios, thus enabling the model to better adapt to diverse imaging conditions and reducing the risk of overfitting. One of the key techniques applied was histogram equalization, which enhances image contrast by redistributing the intensity values of pixels across the image, making anatomical features more prominentand easier for themodelto recognize.

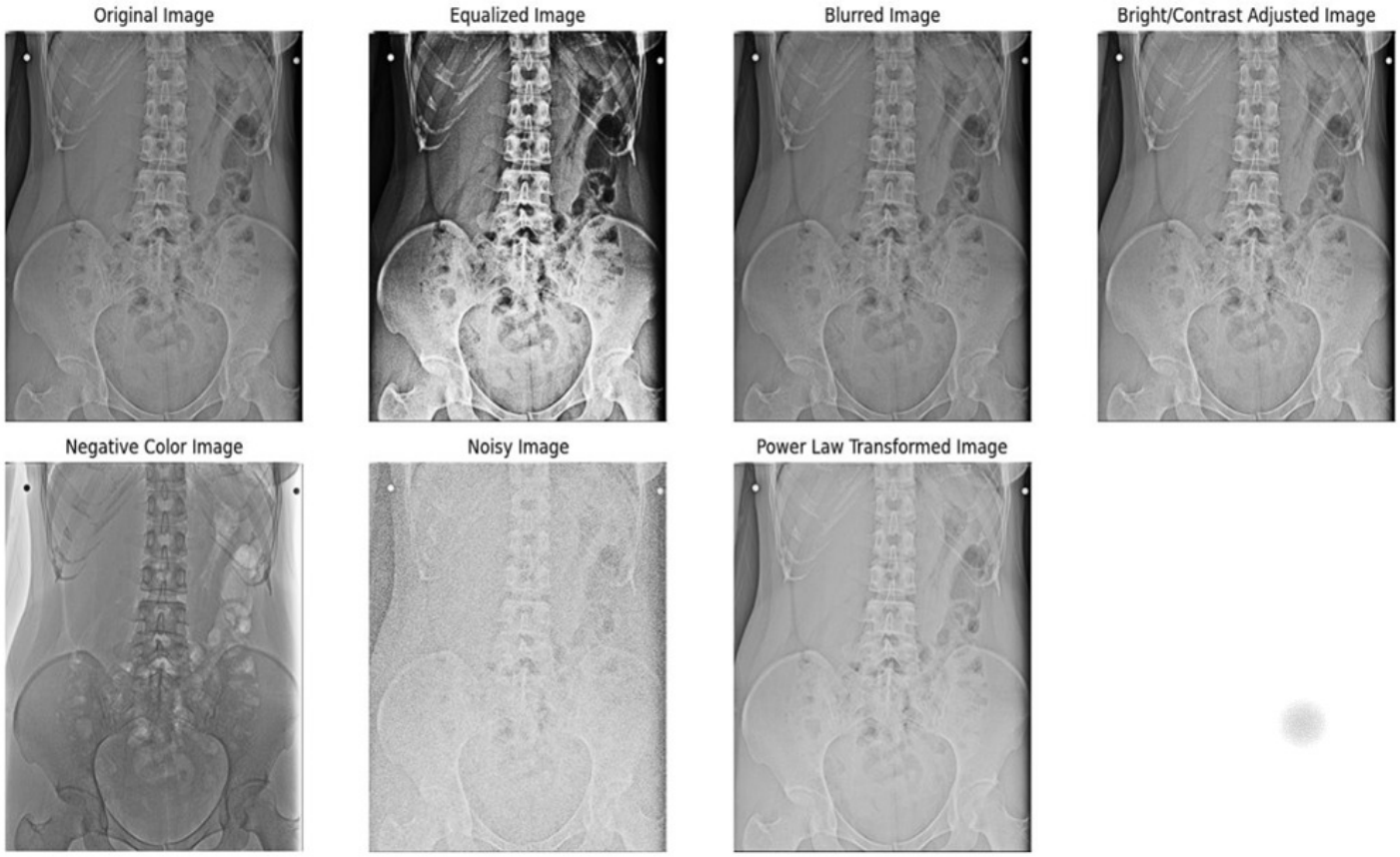


Figure5AugmentedImages

Additionally, Gaussian blurring wasused to smooth theimagesand suppressrandom noise; a 5×5 kernel was applied to average surrounding pixel values, improving segmentation performance in noisy environments. Brightness and contrast adjustments were also implemented using pixel scaling factors—specifically, a contrast factor of 1.2 and a brightness factor of 1.5—thereby improving visibility of soft tissue and bony structures in both underexposed and overexposed radiographs. To further diversify the training data, negative transformation was applied by inverting pixel values, which highlighted featuresthatmayotherwisebesubduedinstandardimaging,suchassubtlevertebraledges.Inaddition,Gaussiannoisewithameanof 0 and a standard deviation of 20 was introduced to simulate variations caused by imaging artifacts and equipment differences, promoting the model's resilience to real-world distortions. Finally, power law transformation (gamma correction) with agamma value of 0.5 was utilized to enhance low-intensity regions of the image, ensuring better detection of faint or poorly visible anatomical boundaries. Collectively, these augmentation methods significantly enriched the diversity of the training set, leading to improved model accuracy, better feature extraction, and higher generalization performance in practical diagnostic applications.

H. SlippageCalculationandMeyerdingClassification

Slippagecalculationplaysacrucialroleinthediagnosisandassessmentof spondylolisthesis,aspinalconditioncharacterizedby the forward displacement of one vertebra over another. The severity of this displacement is quantified using theslippage percentage, calculated by the formula: *Slippage (%) = (Displacement of the vertebra / Width of the inferior vertebra) × 100*. In this context, displacement refers to the horizontal distance by which the upper vertebra has moved relative to the vertebra beneath it, while thewidth of the inferior vertebra is measured along its upper surface. This measurement is fundamental in evaluating the extent of the condition and directly influences clinical decision-making. To systematically categorize the severity of spondylolisthesis, the Meyerding grading system is used. According to this classification, Grade I indicates mild slippage ranging from 0–25%, Grade II involves a moderate shift of 26–50%, Grade III represents a more severe displacement of 51–75%, andGrade IV corresponds to extreme slippage between 76–100%.

The most advanced stage, Grade V, also known as spondyloptosis, signifies a complete dislocation where the upper vertebra has entirely lost contact with the lower one. This grading system is instrumental in guiding treatment strategies; lower-grade slips may be managed conservatively through physical therapy and lifestyle modifications, whereas higher grades, particularly Grades III to V, may necessitate surgical correction to prevent neurological complications and structural instability. Accurate slippage calculation, combined with Meyerding classification, is therefore critical for appropriate diagnosis, prognosis, and therapeutic planning in patients with spinal instability.

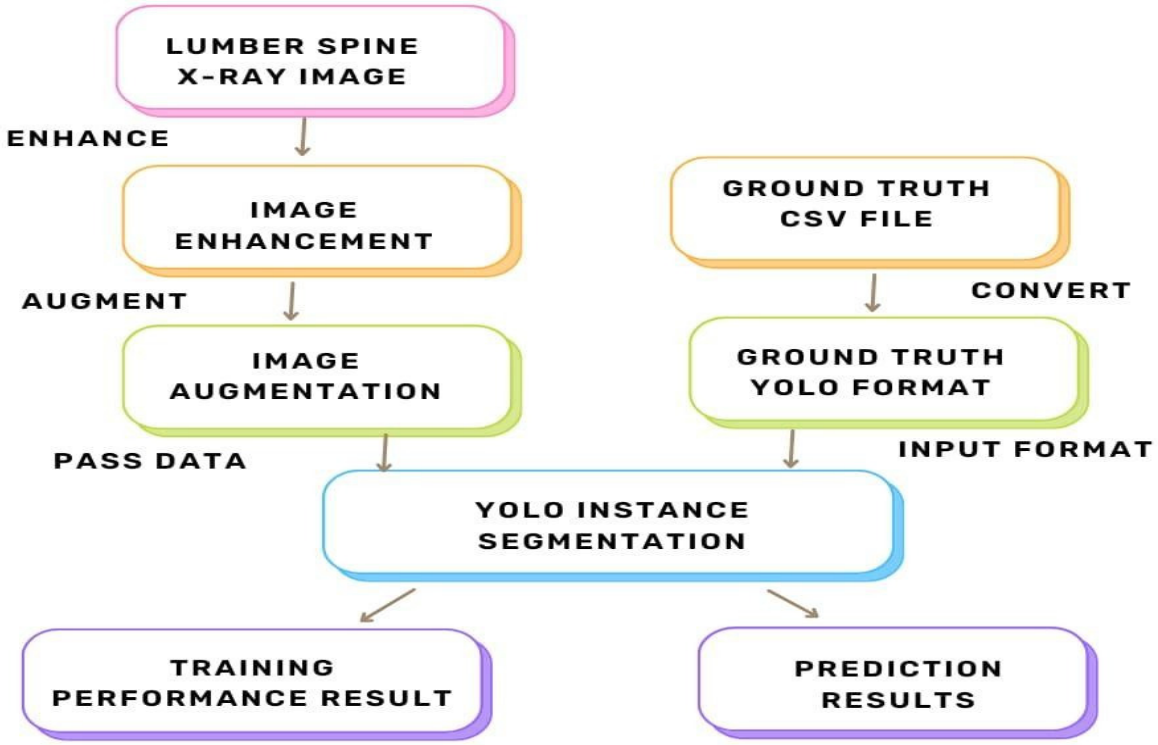


Figure6 Block diagram

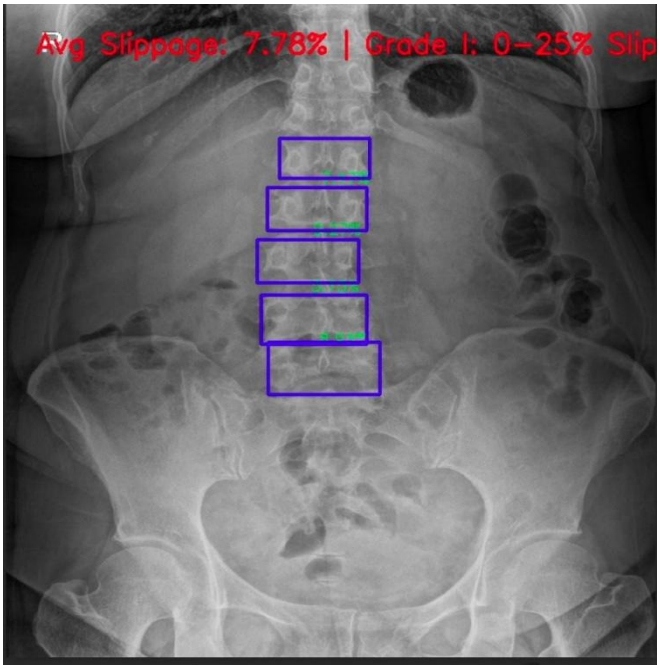


Figure7YOLOv8 Slippage7.78%Grade1 (0– 25%)

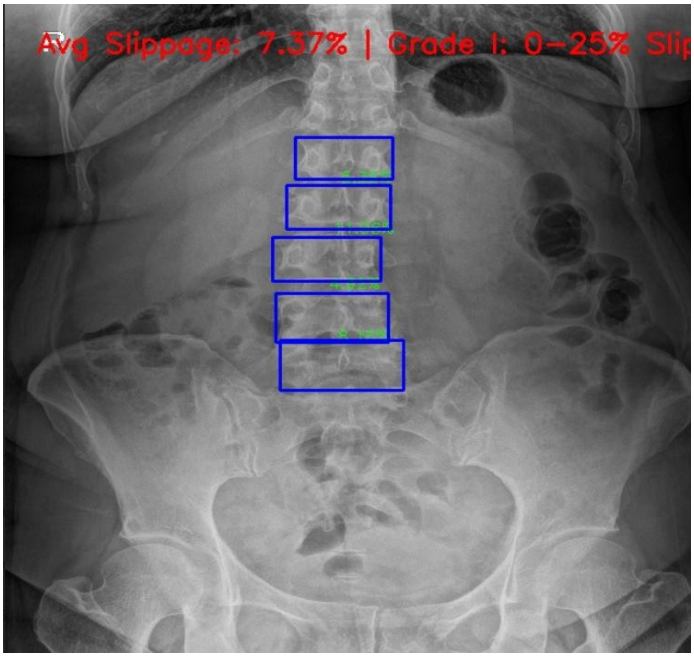


Figure8YOLOv11Slippage7.37%Grade1 (0–25%)

V. EXPEREMENTAL RESULTS

A. Confusionmatrix

The confusion matrix showsperfect classification forL1 to S1,with each class scoring1.00accuracy.Nomisclassifications were observed, as alloff- diagonal values are zero. The model performs consistently across these six classes without any variation.Clear decision boundaries suggest strong learning and separation between categories.

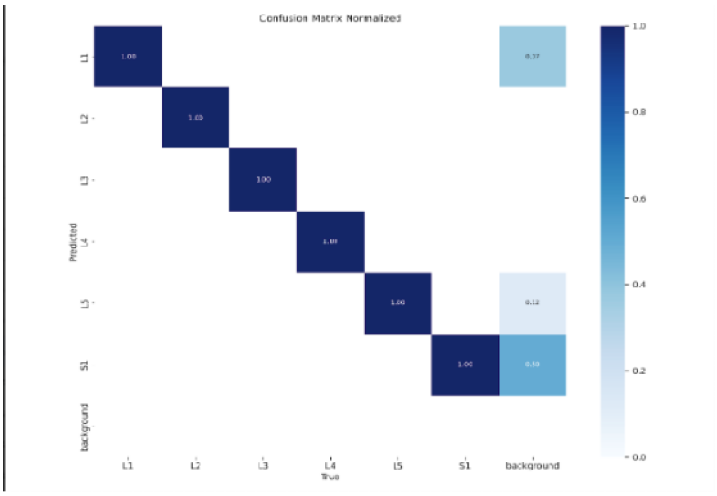


Figure9ConfusionMatrixfor YOLOv8

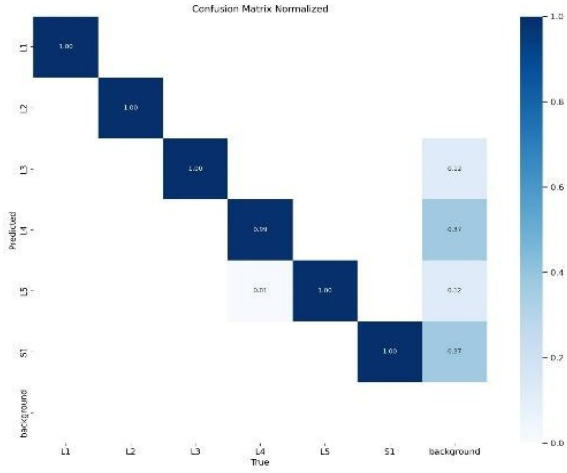


Figure10 ConfusionMatrixfor YOLOv11

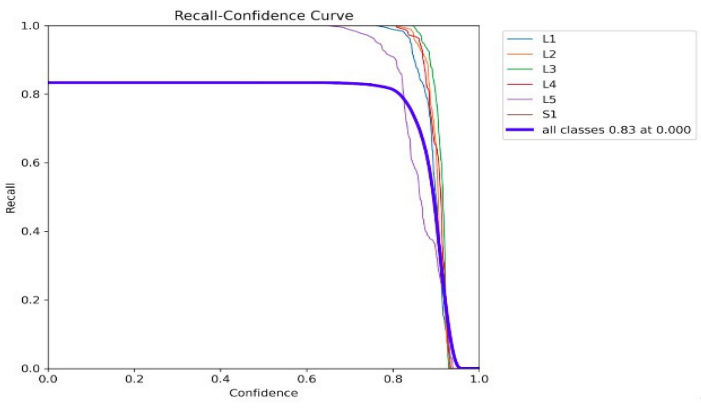


Figure11RecallConfidenceCurve YOLOv8

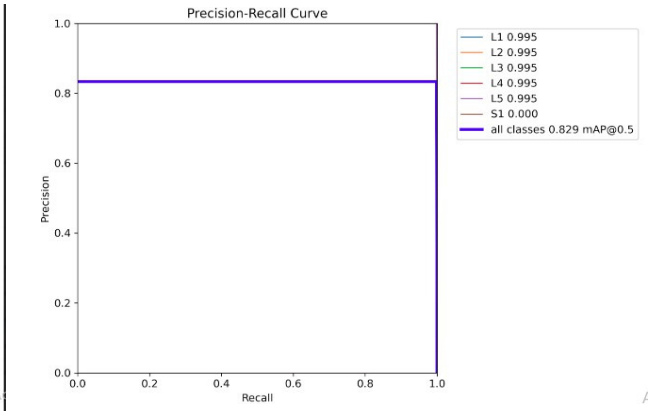


Figure12Precision RecallCurve YOLOv8

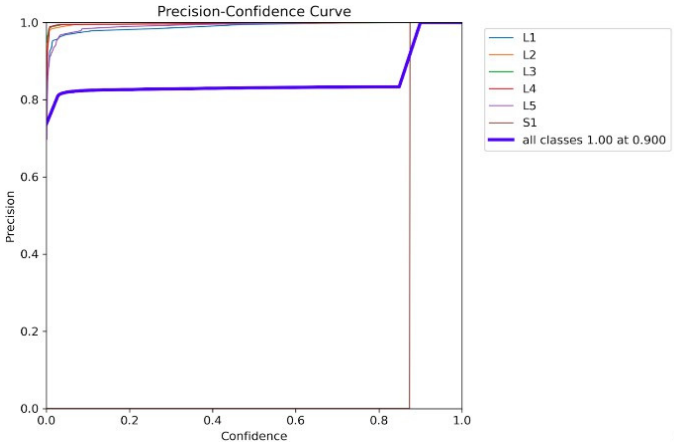


Figure13PrecisionconfidenceCurve YOLOv8

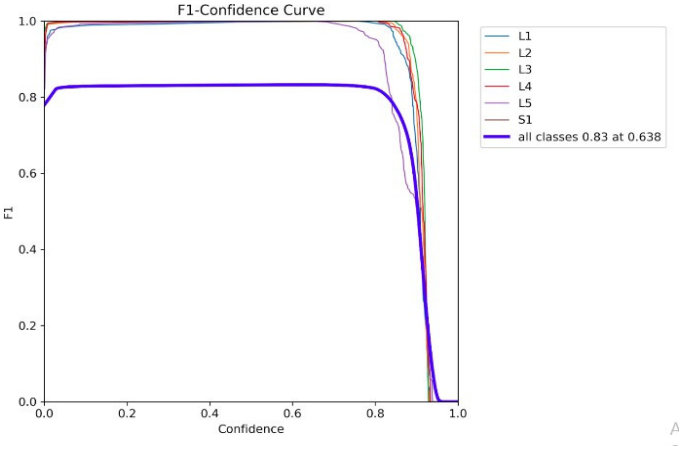


Figure14 F1ConfidenceCurve YOLOv8

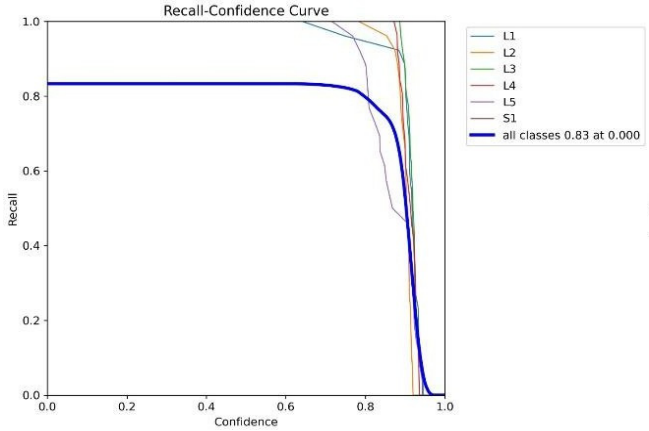


Figure15RecallConfidenceCurveYOLOv11

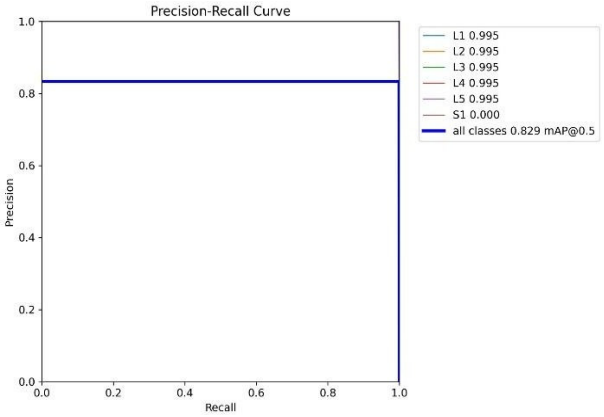


Figure16PrecisionRecallCurveYOLOv11

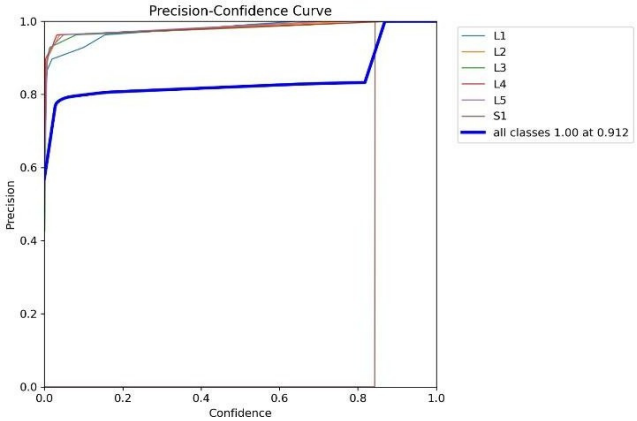


Figure17PrecisionconfidenceCurveYOLOv11

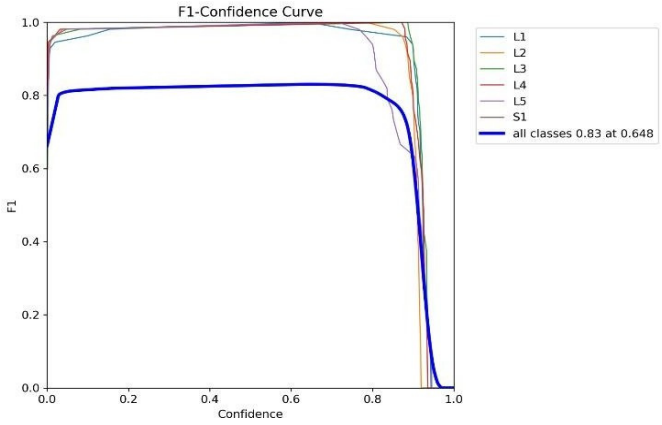


Figure18F1 ConfidenceCurve YOLOv11

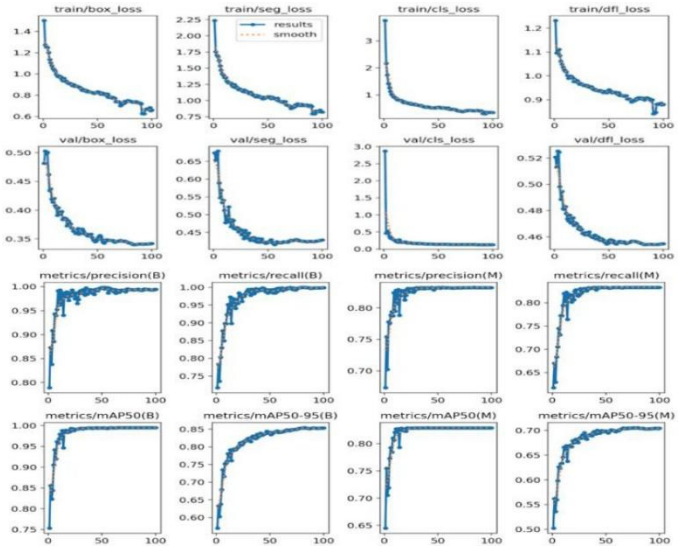


Figure19 YOLOv8

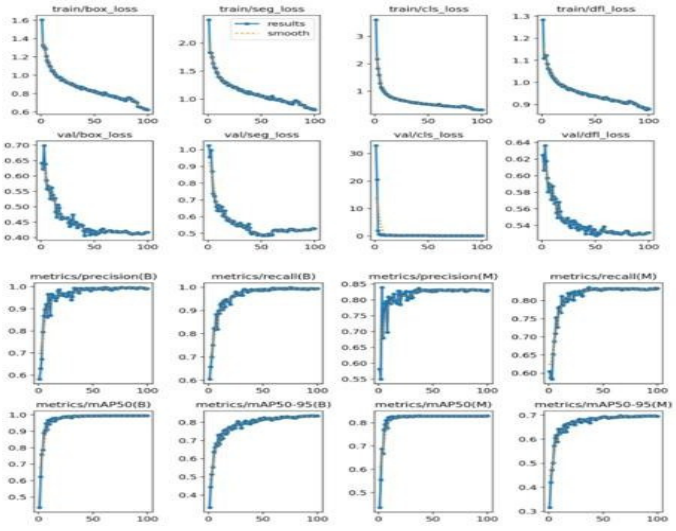


Figure20 YOLOv11

VERSION	IMAGES	BOX				MASK			
		mAP 50	mAP 50-95	recall	precision	mAP 50	mAP 50-95	recall	precision
YOLOv8	Original	0.995	0.833	1	0.992	0.833	0.703	0.828	0.86
	Augmented	0.845	0.832	1	0.993	0.829	0.703	0.833	0.832
YOLOV11	Original	0.998	0.86	0.999	0.989	0.889	0.708	0.833	0.828
	Augmented	0.995	0.856	0.999	0.996	0.83	0.705	0.834	0.833

Figure21Comparison Table

The model exhibits perfect classification for L1 to S1, achieving 100% accuracy with no off-diagonal errors, indicating a strong learning capability but potential overfitting. Performance metrics, including precision, recall, F1-score, and accuracy, confirm the model's reliability, with a mean Average Precision (mAP@0.5)of 0.829. Segmentationperformance showssteady improvement, with losses decreasing over epochs and an F1-score of 0.83 at optimal confidence. Precision-recall and confidence-based curves indicate a well-balanced trade-off, though high confidence predictions reduce recall.

VI. CONCLUSION

This research focused on developing an automated system for detecting spondylolisthesis using deep learning models, specifically YOLOv8 and YOLOv11. The study involved training, validating, and testing medical images while incorporating advanced image processing techniques toenhance model performance. The results demonstrated that although YOLOv11 introduced improvements in architecture and feature extraction, it outperform YOLOv8 in this specific application. YOLOv11 proved to be a more suitable model for spondylolisthesis detection, offering an optimal balance between computational efficiency, accuracy, and speed. The findings validate its effectiveness in medical image analysis and reinforce the potential of deep learning in diagnostic applications. This research highlights the importance of selecting models that align with clinical needs and paves the way for further advancements in AI-driven medical imaging solutions.

Whilethisstudyhasyieldedpromising results,thereareseveralareaswherefurtherresearchand improvementscanbemade:Enhancement of Model Performance – Future work can focus on refining the YOLOv11 model by optimizing hyperparameters, implementing advancedtrainingstrategies, andexploring alternativelossfunctionsto improvedetectionaccuracy.Additionally, experimentingwithhybrid models, such as Vision Transformers (ViTs), may further enhance feature extraction capabilities.Expansion and Augmentation of the Dataset – Increasing the dataset with high-resolution images from diverse sources can help improve model generalization across various patient demographics. The use of data augmentation techniques, including synthetic image generation through generative adversarial networks (GANs), may enhance model robustness and adaptability to real-world medical imaging conditions.Integrationof Multi-Modal Imaging – Incorporating additional imaging modalities, such as MRIandCT scans, alongside X-rayimages couldlead toa more comprehensive assessment of spinal abnormalities. A multi-modal approach may improve diagnostic accuracy by leveraging complementary information from different imaging techniques.Clinical ImplementationandReal-WorldDeployment– Developing acloud-basedormobileapplicationforreal-timespondylolisthesis detection can improve accessibility for healthcare professionals. The integration of the model into a Clinical Decision Support System (CDSS) could assist radiologists by providing AI-driven second opinions, ultimately enhancing diagnostic efficiency and reducing workload.

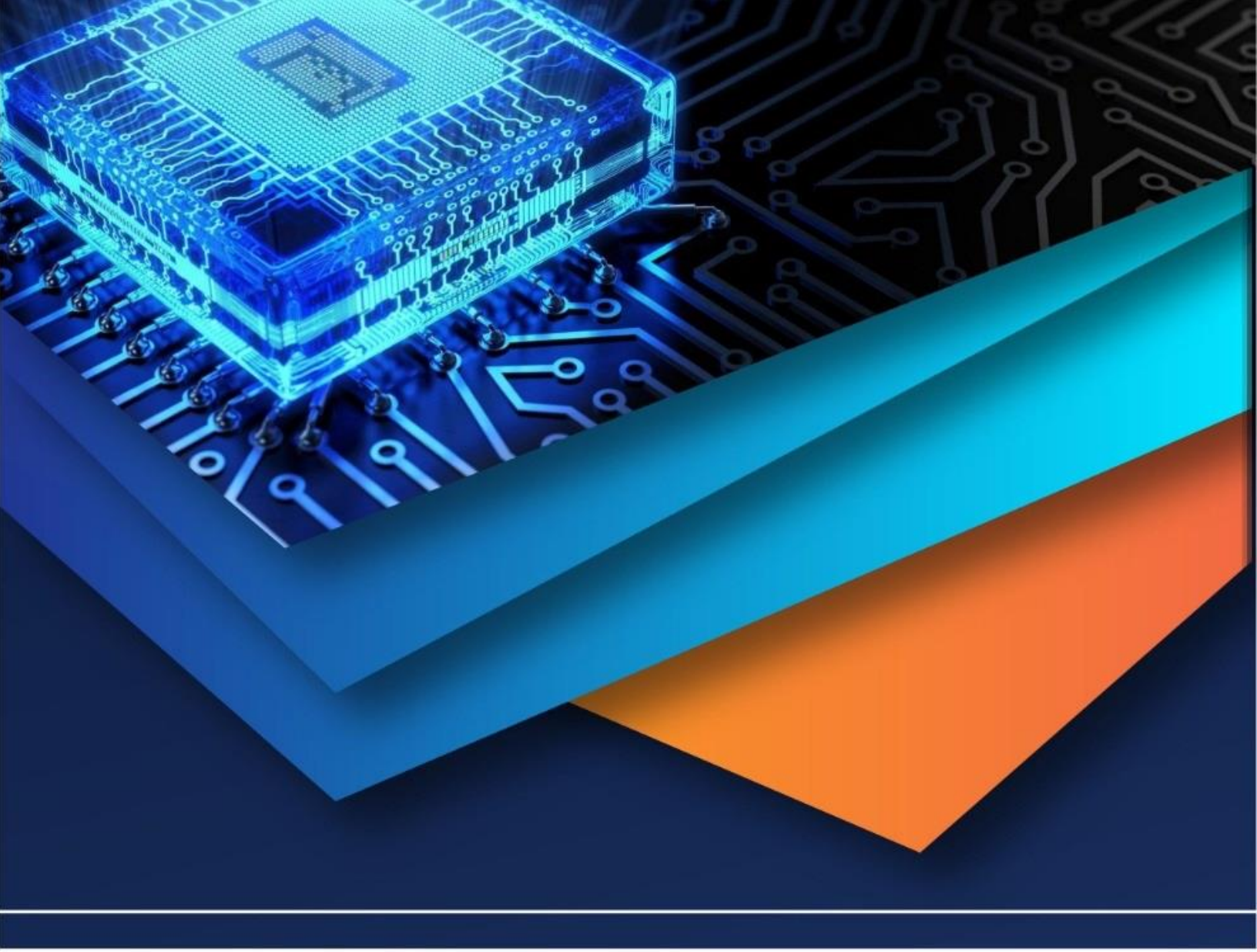
REFERENCES

[1] P.Klinwichit,W.Yookwan,S.Limchareon,K.Chinnasarn,J.-S.Jang,andA.Onuean,''BUULSPINE:AThaiopenlumbarspinedatasetfor spondylolisthesis detection,'' Appl. Sci., vol. 13, no. 15, p. 8646, Jul. 2023, doi: 10.3390/app13158646.

[2] M.Fraiwan,Z.Audat,L.Fraiwan,andT.Manasreh,''Usingdeeptransferlearningtodetectscoliosisandspondylolisthesisfrom Xrayimages,'' PLoS ONE, vol. 17, no. 5, May 2022, Art. no. e0267851.

[3] Nillmani,N.Sharma,L.Saba,N.Khanna,M.Kalra,M.Fouda,andJ.Suri,''Segmentationbasedclassificationdeeplearningmodelembeddedwith explainable AI for COVID-19 detection in chest X-ray scans,'' Diagnos tics, vol. 12, no. 9, p. 2132, Sep. 2022.

[4] A.Bochkovskiy,C.-Y.Wang,and H.-Y.M.Liao,''YOLOv4:Optimalspeed and accuracy ofobjectdetection,''2020,arXiv:2004.10934.
[5] E.Seeram,DigitalRadiography:PhysicalPrinciplesandQualityControl.Cham,Switzerland:Springer,2019.
[6] T.S.Curry,J.E.Dowdey,andR.C.Murry,Christensen'sPhysicsofDiagnosticRadiology.Philadelphia,PA,USA:LippincottWilliams& Wilkins, 1990.
[7] J.R.Balland T.Price,Chesneys'RadiographicImaging.Hoboken,NJ,USA:Wiley,1995.
[8] J.T.Bushberg,J.A.Seibert,E.M.Leidholdt,andJ.M.Boone,TheEssentialPhysicsofMedicalImaging.Philadelphia,PA,USA:Lippincott Williams & Wilkins, 2011.
[9] E.CarverandB.Carver,MedicalImaging:Techniques,ReflectionandEvaluation.London,U.K.:ChurchillLivingstone,2012.
[10] S.Zhao,X.Wu,B.Chen,andS.Li,''Automaticspondylolisthesisgrading fromMRIsacrossmodalitiesusingfasteradversarialrecognitionnet work,'' Med. Image Anal., vol. 58, Dec. 2019, Art. no. 101533.



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