Automatic Detection of Lumbar Spine Disc Herniation

Using Computer Vision and Artificial Intelligence

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***Abstract*—Advanced deep-learning approaches have set new standards for computer vision and pattern recognition. However, the complexity of medical images frequently impedes the creation of high-quality ground truth data. In this article, we offer a method for autonomously generating ground truth data from MRI images using instance segmentation, with a novel confidence and consistency metric to assess data quality. We employ an artificial intelligence-based system to annotate regions of interest in MRI images, leveraging Mask R-CNN—a deep neural network architecture with a mean average precision of 98% for localising and identifying discs. Subsequently, the region of interest is classified with an accuracy of 70%. Our approach facilitates radiologists by automating the detection of regions of interest in MRI images, leading to more efficient and reliable diagnoses with assured quality data. This research made significant advances by developing an automated system for medical image segmentation and implementing cutting-edge neural network technologies.**

Keywords—Lumbar Disc Herniation; MASK-RCNN; computer vision; artificial intelligence; MR Images

I. Introduction

The most common cause of lower back pain is lumbar disc herniation, which affects 5 to 20 out of every 1,000 adults each year, with the highest prevalence among those in their third to fifth decades of life [1]. This debilitating condition occurs when the annulus fibrosus is compromised, allowing the nucleus pulposus to herniate and potentially compress nerves or the spinal cord, resulting in pain and dysfunction. Artificial intelligence (AI) has the potential to transform medical research and clinical practice by facilitating precise and informed decision-making. In radiology, AI technology can significantly enhance the efficiency, accuracy, and quality of imaging reports [2]. Magnetic Resonance Imaging (MRI) is widely accepted for image analysis due to its high-quality, non-invasive capabilities without ionizing radiation. Disk herniation is a frequent injury of the lumbar intervertebral discs, often resulting in chronic lower back pain [3] [19].

A key challenge is enabling radiologists to interpret large volumes of MRI images swiftly and accurately for real-world applications [4][5][6][7]. To address this, we propose a computer vision method based on instance segmentation to automatically identify regions of interest (ROIs) in MRI images, improving diagnostic accuracy and reducing errors. Image segmentation entails partitioning input images into segments that correspond closely with anatomical structures of interest, allowing for extensive examination of medical imaging [8]. Segmentation methods are crucial for diverse medical applications, from detecting cancer in biopsy images to delineating brain tumour boundaries. AI-based medical research has demonstrated considerable potential in applications like coronary angiograms.

Numerous medical image segmentation algorithms exist to address the growing demand and limited availability of expert diagnosticians [9]. Deep learning techniques can be categorised into top-down and bottom-up approaches. Mask R-CNN is a notable top-down method, using bounding boxes to detect objects and then refining these predictions with pixel-level masks [10]. Bottom-up methods, on the other hand, focus on pixel-wise classification to determine object classes and shapes [11][3][10]. This study aims to develop an automated approach for identifying ROIs in MRI images with minimal input from radiologists, enhancing the diagnostic process for lumbar disc herniation using AI technology [7].

II. Related Works

Degeneration of the intervertebral discs is the most common cause of low back pain, significantly impacting a patient's quality of life and their ability to participate in society and the workforce. Consequently, a multidisciplinary approach is often required. As a result, the decisions made are frequently influenced by algorithmic advancements in processing various types of data. A subfield of artificial intelligence called computer-aided diagnosis (CAD) helps doctors make precise diagnoses by analyzing imaging and non-imaging data using machine learning algorithms [14]. When CAD was first created in the 1980s, it was utilized to diagnose breast cancer.

Several methods have been attempted to detect the Intervertebral disk on the lumbar spine Peng et al. [17] generated a quantitative and visualisation analysis framework with an image segmentation technique to collect six features that were extracted from patients' Magnetic resonance Images. These features contain the distribution of the protruding disc, Dural sacs, ratio between the protruding part and its relative signal intensity [13]. Kompali et al. [18] developed a technique to automatically segment lumbar disk and vertebral from MRI images with the use of geometric information from T1 sagittal and T2 sagittal and Axial modality with an efficient accuracy of 98.8% for labelling of the disk on 67 sagittal cases [13].

Today, it is applied to a wide array of fields, such as detecting osteoporosis and identifying lesions missed during colonoscopy. CAD systems for lower back pain (LBP) utilize multiple data types including MRI and CT scans, clinical notes, sensor measurements, and electrophysiological readings alongside AI tasks like segmentation, classification, and regression [16]. Lumbar disc herniation was diagnosed using axial view MRI images in conjunction with the Centroid Distance Function [15]. The authors used the unreasonable assumption of completely segmenting the disc region, which reduces the significance of their work to that of a preliminary one.

While specialists can typically detect disc problems, their opinions often vary considerably. Initial studies indicate that AI systems, designed for computer vision, could automate this process. For example, Won et al. reported a 77.5% accuracy rate and a 75.0% F1 score among specialists when grading spinal stenosis [12] [13]. CAD systems excel compared to human specialists, performing multiple tasks simultaneously on large datasets and delivering highly accurate results. This efficiency allows CAD systems to outperform humans. However, the true potential of AI in CAD systems lies in integrating diverse data sources such as demographics, patient-reported outcomes, clinical notes, and radiological images to produce more accurate diagnoses and enhance patient outcomes. These integrated systems have only emerged in recent years. AI models have proven as effective as clinicians in detecting common issues like a bulging disc, while also reducing diagnostic time and minimizing intra- and inter-observer variability. Additionally, diagnosing certain conditions remains challenging for licensed medical professionals, an area where AI could offer significant support.

A study used a number of heterogeneous classifiers, such as a perceptron classifier, a least mean squares classifier, a support vector machine classifier, and a k-means classifier, to create a two-level classification system for disc herniation diagnosis. For 70 subjects, this framework's accuracy rate was 99% [18]. Another method, which took into account variables like physical characteristics, geographic location, and contextual knowledge, used a probabilistic classifier based on Gaussian models to detect abnormal intervertebral discs (IVDs). Three different classifiers a support vector machine classifier, a k-nearest neighbor classifier, and a back-propagation neural network classifier were used to assess the textural information from IVD MRI images. The results showed an 83.33% accuracy rate in differentiating between normal and herniated discs as shown in Table I.

TABLE I. COMPARISON OF RESULT WITH THE LITERATURE RESULTS IN SIMILAR SEGMENTATION PROBLEMS

Investigated Problem	Author	Results (Map, Dice, IOU, ACC)
Disc Herniation Automatic Detection Using Yolo V3	Jen-yung et al	Map: 92.4%
Automatic detection and classification of disc Herniation	Tijana Sustersic et al	Dice: 0.961
Semi-Auto Segmentation of IVD using Axial View MRI	Mbaki et al	Dice: 0.86
Automatic Diagnose of Disc Herniation in 2-dimentional MR Images Combining Features using Machine Learning	Hamid Yousefi et al	Acc: 97.91% Acc: 97.08%
Intervertebral Disc instance Segmentation using MoM-RCNN	Malinda Vania et al	Sensitivity=88% Specificity on Non-IVD =98%

III. PROPOSED APPROACH

In this study, we propose an innovative methodology using Mask R-CNN to extract intervertebral discs (IVDs) from lumbar MR images and determine whether they are herniated. Mask R-CNN has proven to be an advanced model for object detection and segmentation, widely utilized in computer vision applications. Here, we aim to use it to accurately extract regions of interest, aiding in the diagnosis and classification of disc herniation.

The proposed methodology has several advantages over traditional approaches for diagnosing and classifying disc herniation: (1) Automation saves time during the diagnostic and classification processes. (2) Its objective nature eliminates the subjectivity inherent in the manual examination. (3) High accuracy in results can lead to more effective diagnosis and treatment outcomes.

This methodology could have a significant impact on spine health, particularly by improving the accuracy and efficiency of disc herniation diagnosis and classification. It also has the potential to enhance computer-aided diagnosis (CAD) systems, providing critical support to radiologists when interpreting lumbar magnetic resonance images (MRI).

Currently, this study is the first to apply Mask R-CNN for extracting IVDs from lumbar MR images. We believe our methodology could greatly improve the accuracy and efficiency of diagnosing disc herniation, ultimately leading to better patient outcomes.

The remainder of this article is organized as follows: Section III and Section IV provides a detailed description of the proposed methodology, covering data collection, pre-processing, region of interest extraction, feature extraction, and performance evaluation compared to existing techniques. Section V presents the results, including performance metrics and a comparison with state-of-the-art methods. Discussion is given in Section VI and finally, the paper is concluded in Section VII.

Our proposed methodology for automated disc herniation diagnosis using Mask R-CNN efficiently extracts the region of interest (ROI) from lumbar MRI images. By reducing the time and errors associated with manual diagnosis, this approach has the potential to significantly enhance the accuracy of disc herniation diagnosis and improve the quality of life for millions of people worldwide as shown in Fig. 1.

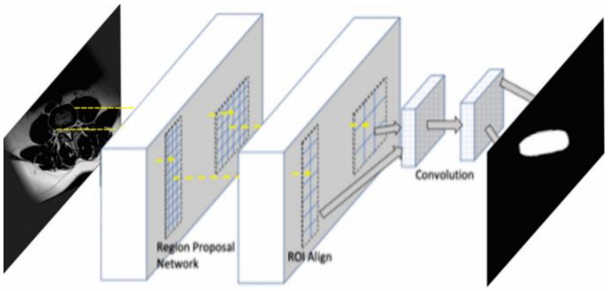

Fig. 1. Overview of mask RCNN framework.

IV. Data Collection and Pre-Processing

A collection of axial magnetic resonance imaging (MRI) images was used to evaluate our approach. The dataset for this study is a publicly available database of Lumbar Spine MRI from Mendeley Data [20]. Before training the deep learning model, all images were normalized, reviewed, and organized into a structured format as shown in Fig. 2. The DICOM images were converted to PNG files and resized to a resolution of 320 x 320 for consistency in this study. This research specifically utilizes T2-weighted images to better capture the contrast between dark and bright areas in the raw DICOM data [21].

Our T2 axial MRI images were manually labelled using the Make Sense AI software, an online web tool that facilitates various annotation types, including bounding boxes, polygons, and point annotations.

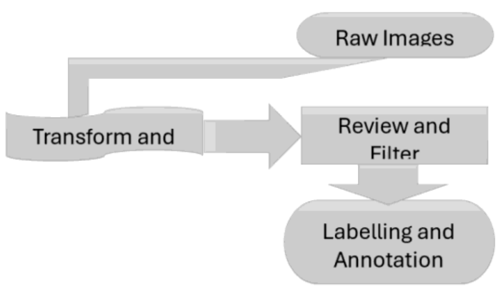

Fig. 2. Flow diagram for data pre-processing.

A. Data Annotation

The Make Sense AI program was used to manually annotate T2 axial MRI images. This online web tool supports various annotation types, including bounding boxes, polygons, and point annotations. Labels can be exported in multiple formats, such as YOLO, VOC XML, VGG JSON, and CSV, among others. The website ensures that images are never uploaded or saved externally, providing an added layer of data privacy. No installation is required to use the tool. Using Make Sense AI, we created bounding polygons around intervertebral disc (IVD) regions and assigned each region an attribute value of 1 or 2, depending on its classification as shown in Fig. 3.

B. Instance Segmentation Using Mask-R-CNN

Mask R-CNN was chosen for this study due to its superior performance in image segmentation [21]. Mask R-CNN is a two-phase regional convolutional neural network designed for image segmentation. In the first phase, the Region Proposal Network (RPN) processes the image to generate candidate bounding boxes, which are then passed to the second phase. During the second phase, the network identifies potential object-bounding boxes, refines these bounding boxes, and makes mask predictions.

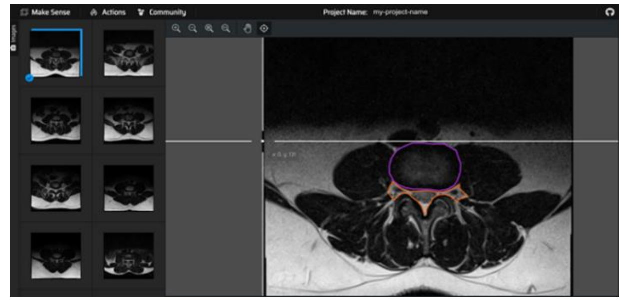

Fig. 3. Flow diagram for annotations.

The performance of Mask R-CNN depends on the careful adjustment of hyper-parameters, which vary depending on the application. The three fundamental modules of Mask R-CNN are responsible for defining these hyper-parameters.

C. Backbone

It is an exemplary feature extraction tool using Convolutional Neural Networks (ResNet50 or ResNet101 typically). Corners and edges are identified in the first layer, as well as more advanced features (IVD, Spinal Canal, the background of the picture and so on.) are identified by subsequent layers. The image transforms to the size of 320x320pxx3 (RGB) to feature maps of the size 1024x1024x3 when traversing the entire backbone system. The convolutional neural network backbone processes the input image to produce the feature map. The input for the succeeding steps is this feature map. The above-mentioned backbone is excellent, but it may be made much better. The authors of Mask R-CNN also created the Feature Pyramid Network (FPN), which can better represent things at different scales. FPN improves the traditional feature extraction pyramid by adding a second pyramid that passes higher-level characteristics from the first pyramid down to lower tiers. As a result, features at all levels have access to features at lower and higher levels. Our Mask RCNN implementation uses the ResNet 101+FPN backbone [22].

D. Regional Proposed Network (RPN)

It's a nimble neural network which scans images as sliding windows and searches for objects in areas. The RPN analyses what are called anchors. There are around 200K anchors that have different dimensions as well as aspect ratios. To cover every inch of the image as possible, they must. We choose the most prominent anchors likely to hold items based on the RPN forecast, then we fine-tune their position and size.

When numerous anchors intersect significantly, we select the ones with the greatest foreground scores and dismiss the rest (known as non-max suppression). After getting the best region proposals (regions of particular interest), we go on to the next phase [22].

- RoI Classifier and Bounding Box
- Segmenting Region of Interest

E. ROI Classifier and Bounding Box

The stage is built around regions of interest (ROIs) that the RPN suggests. Like the RPN, this stage produces two results for each ROI.

- Class: The kind of object contained within the ROI. Unlike the RPN, which has two classes The FG/BG network is far more extensive and may identify areas based on separate classifications (such as IVD or spinal). Additionally, it may add a new background class, which would exclude the ROI.

- Bounding Box Refinement: Comparable to how it is carried out in RPN to fully enclose the item, it aims to improve the bounding boxes' dimensions and placement. Classifiers struggle to handle inputs of different sizes. They typically need a set quantity of input. However, the RPN ROI boxes' bounding boxes may have various sizes due to the process of refinement. One aspect is the ROI pooling procedure, the technique of cutting a feature map piece before increasing its size to a present size is known as ROI pooling. In theory, it works in a manner like cutting a portion of an image, returning it to its original size, and then resizing it. The ROI Align approach has been proposed by the developers of Mask R-CNN. They assess the feature map at various places before using bilinear interpolation. Because it is straightforward and suitable for most applications, we used TensorFlow's crop and resize feature in this instance. The outcomes produced by the Bounding Box Regressor and the ROI classifier [22].

F. Segmenting Region of Interest (IVD)

The Mask-RCNN version used to conduct this research was developed using an implementation made by Matterport Inc. [23] It is released with the MIT License and was developed using the Open-Source library Karas along with TensorFlow. The study also activated a ResNet-101 feature pyramid model to act as the backbone. Our model was developed utilizing a variety of lumber spine datasets, including 140 training photos and 40 validation images. Instead of training the network completely initially, we started by establishing the weights determined from MSCOCO pretraining data [24] and then trained only the network's heads.

Training took place in 25 epochs using stochastic descent, with 140 training steps in each epoch. The maximum learning rate was set at 0.001 and the momentum at 0.9. This is done with an average batch size of two for only one NVIDIA GPU. The mean average precision during training was 98.2%, and during validation, it was 97.5%. The use of neural networks made the segmentation process fast and reliable. Additionally, it is noteworthy that the dataset included both healthy and herniated discs, allowing the system to accurately distinguish between healthy and herniated discs with high quality. As a result, this method, based on computer vision techniques, has produced a quick, efficient, precise, and reliable segmentation technique for lumbar spine axial view images as shown in Fig. 4.

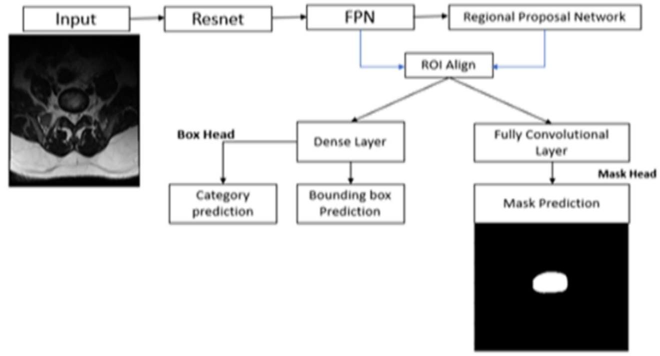

Fig. 4. Flow diagram for model architecture.

G. Metrics for Evaluating Performance

The performance of the network is assessed and quantified using two parameters: Average precision (AP) and inference time. This refers to the time it takes for the network to make the forecast [23].

H. Detecting Threshold

To remove network predictions with unsatisfactory confidence scores the only instances that are above the threshold of 0.9 will be considered for the result [23].

I. Average Precision (Ap)

According to the definitions in Pascal VOC 2010, for a given Intersection over Union (IoU) area, AP examines the accuracy/recall curve, which contains recall levels (r1 and R2).) where the most precise falls. The highest point of perfection. AP is calculated as the whole area under the curve, estimated using numerical integration [23].

$$AP = \sum n(rn + 1 - rn) \cdot pinterp(rn + 1)$$

Equation 1: Average precision (Ap)

Where: rn and rn+1 are successive recall levels.

Pinterp (rn+1) is the interpolated precision at recall level rn+1.

(rn+1−rn) represents the change in recall between

two consecutive recall levels

V. RESULTS

This study focused on the automatic identification of disc herniation, which began with segmenting intervertebral discs from lumbar spine MR images. The segmentation process achieved a 100% detection rate as shown in Fig. 5 and an average precision of 98.2%. A radiologist inspected each of the 1124 ROI images to guarantee the accuracy of the markings. Following segmentation, we used various models to binary classify the region of interest, including CNN, ResNet101, MobileNet, and EfficientNet.

Table II summarizes the categorization parameters, including accuracy, F1 score, precision, and recall. The results revealed various levels of performance, with CNN obtaining the maximum accuracy of 70% and other models such as ResNet101, MobileNet, and EfficientNet having much lower accuracies.

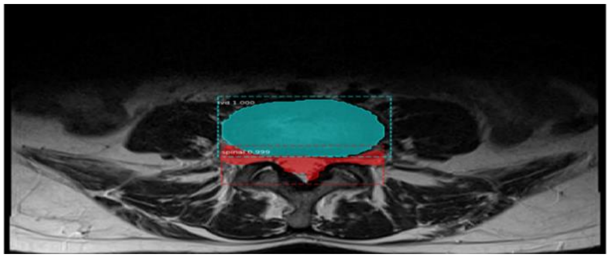

Fig. 5. Detection rate 100%.

TABLE II. COMPARISON OF RESULTS OF DIFFERENT MODELS TESTED

Models	Accuracy (%)	F1 Score	Precision	Recall
CNN	70	0.77 0.57	0.62 1.00	1.00 0.40
ResNET101	50	0.67 0.00	0.50 0.00	1.00 0.00
MobileNET	50	0.67 0.00 0.67	0.50 0.50	1.00 0.00
Efficient NET	50	0.00 0.00	0.00 0.00	1.00 0.00

VI. DISCUSSION

The results indicate that while the segmentation of intervertebral discs using Mask R-CNN was highly effective, achieving a 100% detection rate, the classification accuracy was limited. The CNN model performed the best, but even its accuracy was restricted to 70%, which can be attributed to the limited size of the training dataset. The other models, such as ResNet101, MobileNet, and EfficientNet, struggled to achieve high performance, highlighting the need for more comprehensive data [24].

Overfitting emerged as a challenge due to the small dataset size. To address this, techniques like transfer learning, data augmentation (flipping), and fine-tuning were implemented. However, these measures alone were insufficient. Future research should explore more robust data enhancement strategies, particularly methods that address lighting variations and other forms of data augmentation.

Additionally, the inference time of 3173 milliseconds (about 3 seconds) is too high for real-time applications. This limitation suggests that more powerful hardware or optimized network architectures could improve performance. Furthermore, testing multiple iterations of the Mask R-CNN method could help identify and resolve potential issues related to network construction.

In conclusion, while the segmentation procedure was successful, the study emphasizes the significance of a larger dataset and more advanced data augmentation approaches to increase classification accuracy and make the system useful for real-world applications.

VII. CONCLUSION

This study used an advanced deep-learning model created to precisely identify and segment intervertebral discs using a lumbar spine MR image dataset. Its performance was reflected in a mean precision of 0.982 by a record of 3175 milliseconds making use of a small amount of data as well as a transfer-learning technique. Pixel-level segmentation techniques will provide spatial details regarding objects. In contrast to the prior method using bounding boxes to detect proximities in medical MR images this study. Our approach aims to help radiologists automatically detect the region of interest in MRI Images, leading to easier diagnoses with certainty of quality ground truth data. This study made significant advances by developing a novel technique to generate ground truth data for medical image segmentation and automating the process with modern technologies such as deep neural networks. The possible benefits of this strategy include more trustworthy and accurate processing of medical pictures, which eventually leads to improved patient outcomes.

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