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Pipelined Multilayer AI-Based Point-of-Care Model for Diagnosis of Spinal Cord Disorders in Big Clinical Data

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ABSTRACT
The disorders in the spine reduce the quality of human life therefore large clinical data with scanned spinal cord images can be processed by AI-based point-of-care services to quickly and accurately diagnose spinal cord problems such as lumbar spinal stenosis, spinal deformities and spinal osteoarthritis. Vertebrae localization and segmentation are essential in the accurate diagnosis of spinal cord disorders. However, the existing labelling and localization process for scanned images of the spinal cord is not suitable for large clinical data corroboration from numerous patients and has erroneous label findings due to missed vertebrae that were only partially visible on the image, similar forms of vertebrae in cervical, thoracic, and lumbar regions, as well as labelling process, failed to detect sacrum. Also, localization error occurs especially in spinal cord images with anatomical abnormalities such as additional and transitional lumbar vertebrae, it is difficult to properly locate vertebrae in the mid-thoracic area. So, there is a need to develop a novel AI-based point-of-care model for large clinical scanned spine images to effectively diagnose various spinal cord disorders at an early stage to provide timely treatments with accurate labelling and segmentation of spinal cord components.
The proposed AI-based point-care-model uses Pipelined labelling with level count Circular Localization, and then Feature Transformer based Classification which effectively diagnoses various spinal cord disorders with its sublevels at an early stage with accurate labelling, segmentation and feature extraction on the localized spinal cord components.

KEYWORDS
Deep learning, point of care, AI, Hough line transform filtering

1. INTRODUCTION

Point-of-care technology (POCT) enables quick clinical decision-making by providing actionable information at the point of care. POCT refers to the devices or services that are used to offer clinical decision support and give quick laboratory results in real-time. The outcome from POC devices was uploaded to laptops that were used across the hospital. With the aid of that information, laboratories could determine the quality of clinical data and diagnose diseases with better clinical decision-making [1,2]. Hence, in order to enhance the outcome in evaluating the potential of health care, a simple yet effective and scalable large data analysis system can be used. Artificial intelligence (AI) has been employed more frequently in diagnostics in recent years. AI may be easily included in POCT in clinical pathology to maintain the quality of big clinical data and to produce effective findings when interpreting diseases via automated diagnostic classifiers [3-5]. The most common reason for adult clinical visits in contemporary cultures is back pain, which is brought on by ailments including spondylolisthesis and spinal stenosis, incurring significant costs and reducing living quality and job performance [6]. Hence, it is necessary to diagnose spinal cord disorders from large clinical scanned images at an early stage with the point-of-care.

Machine learning (ML) and deep learning (DL) techniques are broadly used in the prediction and diagnosis of spinal cord disorders that include spinal oncology, spinal osteoarthritis, trauma, infections, degenerative diseases, and adult spinal deformity. Spinal osteoarthritis, Lumbar Spinal Stenosis (LSS) and spinal deformities are the leading cause of back pain [7,8]. Spinal osteoarthritis often known as non-inflammatory or degenerative arthritis develops over time and usually affects the lower back in which inflammation and pain are caused by the gradual breakdown of the cartilage between the joints. Scoliosis is a three-dimensional deformation of the spine that affects a large portion of the population and is more common in women than in males. Because of this, it is considered catastrophic and should be diagnosed early to prevent major issues with the spinal intervertebral column. One of the main causes of ongoing lower back discomfort is LSS. This is a constriction of the lumbar spinal canal caused by swelling of the soft tissues or bone, which puts pressure on the spinal nerve roots. Patients will experience symptoms like neurogenic claudication, neuromuscular pain, and unusual leg pain. For predicting these spinal cord disorders with an early-stage alert, ML and DL techniques process large clinical datasets containing spinal radiography images, computer tomography (CT) images and magnetic resonance imaging (MRI) images with effective segmentation and classification [9-11]. Segmentation of spinal cord images has been previously done with the fuzzy c-means method (FCM) and other soft segmentation approaches. The quantification of disc degradation, computer-aided disease diagnosis, and computer-assisted spine surgery would all benefit from the correct segmentation of intervertebral discs [12,13]. However, none of these studies provided quantitative segmentation accuracy evaluation results.

Automatic DL methods such as CNN, U-Net and DNN for spinal cord disorder detection on a large clinical CT, radiography and MRI images might notify the reporting radiologist and clinicians, enabling a speedy decision for confirmation and therapy planning of spinal cord disorders. By doing so, the need for medical resources would be lessened and earlier treatment might be given to prevent neurological impairment that is irreversible. Prior deep learning in spine CT, radiography and MRI has shown considerable potential, especially for the identification of lumbar spinal stenosis, deformity, and spinal osteoarthritis. Deep learning is still in its infancy when it comes to the identification and classification of spinal cord disorders on CT, radiography and MRI. It now focuses mostly on detection, bone segmentation, and metastatic load [14-16]. Although, the existing segmentation and detection approaches for spinal cord disorder prediction fail to produce a high detection rate and dice coefficient with erroneous labelling and localization of spinal cord components. Also, they failed to determine more than one spinal cord disorder at a time due to the processing of limited clinical data and unique characteristics related to diverse disorders are not extracted. Hence there is a need to propose a novel AI-based point-of-care diagnosis model to effectively detect various spinal cord disorders by processing large clinical data images.

2. LITERATURE SURVEY

Al-kafri et al [17] described a method for semantic segmentation and MRI determination of the lumbar spine using deep learning to assist doctors in detecting stenosis of the lumbar spine. MRI scans from 515 patients with symptomatic back pain are included in this dataset. Expert radiologists make annotations on each study describing the lumbar spine's observed characteristics and state. Also, created an evidence truth dataset with labels for four key lumbar spine areas, which

was utilized as training and test pictures for segmentation classification algorithms. Based on the Jaccard index, two new metrics have been developed to assess the quality of the evidence dataset: validity and consistency. Using SegNet, tried out semantic segmentation. However, the mean accuracy in segmentation is consistently lower in the unregistered class.

Mushtaq et al [18] discuss the localization and segmentation of the lumbar spine, which aid in the analysis of lumbar spine abnormalities. YOLOv5, the YOLO family fifth variation, is used to locate the lumber spine. Then, linked the angles with the region size calculated from the YOLOv5 centroids to identify the lumbar lordosis and achieved a 74.5% accuracy. Acquisition of segmented vertebrae and ribs, cropped images from YOLOv5 bounding boxes are sent through HED U-Net, a system that combines edge detection and segmentation. After using the Harris corner detector with extremely minimal mean errors to find the corners of the vertebrae, the lumbar lordotic angles (LLAs) and lumbosacral angles (LSAs) are discovered. However, as the localization and segmentation process become more difficult, a completely automated machine learning toolset for spinal abnormalities is required in order to avoid invasive surgical procedures.

Chae et al [19] presented an automated method for precisely measuring spinopelvic parameters using a decentralized convolutional neural network in order to replace the current manual process, which not only necessitates skilled surgeons but also has processing limitations due to the explosion of big data technologies. The suggested approach involves gradually constricting the regions of interest (ROIs) for feature extraction, which causes the model to concentrate primarily on the crucial geometric properties represented as key points. Utilizing decentralized CNN involves distinct datasets, which must be given specifically for each order. As a result, it takes time to create the datasets as well as train the CNN models thoroughly. Although, the failure in detection arose because the L5 vertebra and sacrum's positions were incorrectly anticipated by the ROI detection stage of the second-order ROI detection model.

Rehman et al [20] use the probability map of a pre-trained deep network to initialize the level set and refines the output repeatedly under the operation of multiple factors. As a result, the network's learning ability is increased, and the network can accept large topological form changes in the vertebrae. On two separate datasets, the proposed technique was tested. The first is a collection of 20 publicly accessible 3D spine MRI datasets for disc segmentation, while the second is a set of 173 computed tomography scans for segmenting thoracolumbar (thoracic and lumbar) vertebrae.

U-Net architecture, on the other hand, fails to perform and obtain suitable segmentation performance when dealing with segmentation situations with substantial topological shape variability.

Zhang et al [21] proposed a two-phase study with an exploration group of 120 Adolescent with idiopathic scoliosis (AIS) and a validation cohort of 51 AIS with mean Cobb angles of 23° and 5.0° at the first visit each. In order to create a composite model for prediction, patients with AIS were tracked for a minimum of six years. Clinical parameters were gathered on the initial visit from standard clinical practice, and blood was tested for circulating markers. The composite model has a larger area under the curve than do the individual factors currently employed in clinical practice. The model had a sensitivity of 72.7% and a specificity of 90% after being validated by a separate cohort the initial study to propose and validate a prognostic composite model based on clinical and circulation characteristics that could objectively assess the likelihood that an AIS curve would proceed to a severe curvature. The study did not, however, address the connection between the success of the medical intervention and the severity of the disease.

In order to determine the extent of the damage and forecast the illness patterns on the excessively segmented regions and features, a novel segment-based classification model has been proposed by Ahammad et al [22]. The spinal cord areas in the current model are segmented using a hybrid image threshold method in order to employ a non-linear SVM classification strategy. The suggested threshold-based non-linear SVM exhibits superior accuracy for spinal cord injury (SCI) detection than the conventional feature segmentation-based classification models. However, this model has to precisely maintain its performance in terms of accuracy and error rate. Additionally, the noises in the T1-weighted and T2-weighted regions are not optimized.

From the analysis, it is noted that [17] the average segmentation accuracy is consistently low in the unregistered class, [18] has high computational complexity, and [19] has an error in detection. In [20], segmentation performance degrades with substantial topological shape variability, [21] provides very less information for clinical decision making and [22] has noise in the T1-weighted and T2-weighted regions.

3. RESEARCH GAP

Erroneous label findings due to missed vertebrae that were only partially visible on the image, similar forms of vertebrae in cervical, thoracic, and lumbar regions as well as the labelling process failed to detect sacrum.

Localization error occurs especially in spinal cord images with anatomical abnormalities such as additional and transitional lumbar vertebrae, it is difficult to properly locate vertebrae in the mid- thoracic area.

Existing semantic and automated segmentation approaches have rough image details since they require annotations in the form of bounding boxes and the position of the target region thereby the intervertebral disc, sagittal region, and spinal canal are missed in segmentation results.

Existing models diagnose single spinal cord disorder with its limited scanned images and they did not extract significant angular, curvature, structural and distance features which result in misclassification because the region-area-based method depends on the centroids of multiple vertebrae and even a small error in the centroids' computation affects the entire area.

4. PROBLEM STATEMENT

Point-of-care technology (POCT) facilitates quick clinical decision-making by facilitating access to crucial and pertinent information at the point of care. Recent trends in medical research state that there is a significant transition in the healthcare systems towards the precision medical drug, public health, and chronic disorder management. This has increased the potential effect of POCT and various important POCT techniques have been introduced within the last decade and most medical researchers have suggested different enhancement techniques. The POCT helps in evaluating the importance of healthcare for patients, payers, providers, and suppliers. However, it is highly difficult and challenging to measure the value of healthcare. It requires efficient, robust, systematic, and empirical measures which allow the analysis of scientific objectives. Enhancing the outcome after surgical procedures and evaluating the potential of health care can be achieved using a simple yet effective and scalable data outcome collection system. Artificial intelligence, machine learning, deep learning, expert systems, and neural networks have all recently been used more and more in diagnostics. AI may easily be applied with POCT devices in clinical pathology to give effects interpretation or diagnosis. Conventional laboratory testing results are used as a general measure to validate the efficiency of AI algorithms.

There are several potential challenges to successfully developing, validating, and implementing enhanced POCT. The most frequent obstacles are a lack of a sufficient or exact match between skills and clinical demands, or a lack of awareness of how clinical care is provided. Clinical requirements assessment should be given early priority and often revisited at crucial stages of technology development to get around this obstacle. Another barrier is the lack of demonstration of the clinical usefulness and user user-friendliness with a focus on the technology alone. Concerns about POCT's quality are another issue. The assays used are frequently more susceptible to interference than conventional laboratory tests and are typically less analytically sensitive than assays carried out in the central laboratory. In addition to these problems, this study identifies some of the prominent challenges which can be summarized as follows:

- There is constrained evidence to illustrate whether the implementation of POCT testing translates into significant patient effects in low-resource settings.
- POCT incorporates various disadvantages or limitations such as incorrect handling and/ or maintenance of the analyzers by non-trained clinical staff, inadequate or even absent calibrations and/or quality controls.
- Lack of economics brought on by a growth in the number of analyzers and the price of reagents, as well as inadequate paperwork. Comparing the resulting POCT results to standard laboratory findings is challenging.

Other difficulties with POCT exist, primarily in the area of quality control. Clinical workers rather than those with laboratory training perform POCT, which increases the risk of mistakes since they are less aware of the value of quality control and quality assurance procedures. Additionally, it can be concluded that POCT does not ensure better patient outcomes. In most cases, POCT offers test results with a quicker turnaround time. The entire clinical pathway needs to be optimized if clinical management is to be accelerated successfully. Although it is not the only element in this final analysis, a quicker test result can help patients have better outcomes.

5. PROPOSED SYSTEM

In figure 1. Large clinical data with spine MRI, CT and X-ray images are processed using a novel Pipelined labelling with level count Circular Localization in which IIR – Hough line transform filtering increases the resolution of images with improved edge detection thereby all vertebrae are visible in the image and the similar forms of vertebrae are labelled separately as cervical/lumbar vertebrae and thoracic/sacrum via pipelined stochastic convolutional labelling NN in which one stage fetch of labels feasibly maintain labelling of different images without failure in sacrum detection. Also, the additional and transitional lumbar vertebrae are determined using Level check counter NN and the vertebrae are localized properly in all areas of the spinal cord component with its circular anisotropic localization mechanism thereby eliminating localization error. These localized spinal cord components are segmented using Multi-Atlas Instance SegNet which provide smooth image details with high dice score in segmenting the intervertebral disc, sagittal region, and spinal canal. Moreover, to effectively diagnose spinal cord disorders at an early stage a novel Domineering Feature Transformer-based Classification has been proposed in which cobb angle, the area between the anterior and posterior vertebra, end plate angle, local curvature, bone structure and intervertebral distance are extracted using Visual bipartite matching loss feature transformer and the various spinal cord disorders such as lumbar spinal stenosis, spinal deformities and spinal osteoarthritis are classified with its sub-levels based on Bilsky Phenotype grading classifier without centroid detection thereby enhance the detection rate without misclassification.

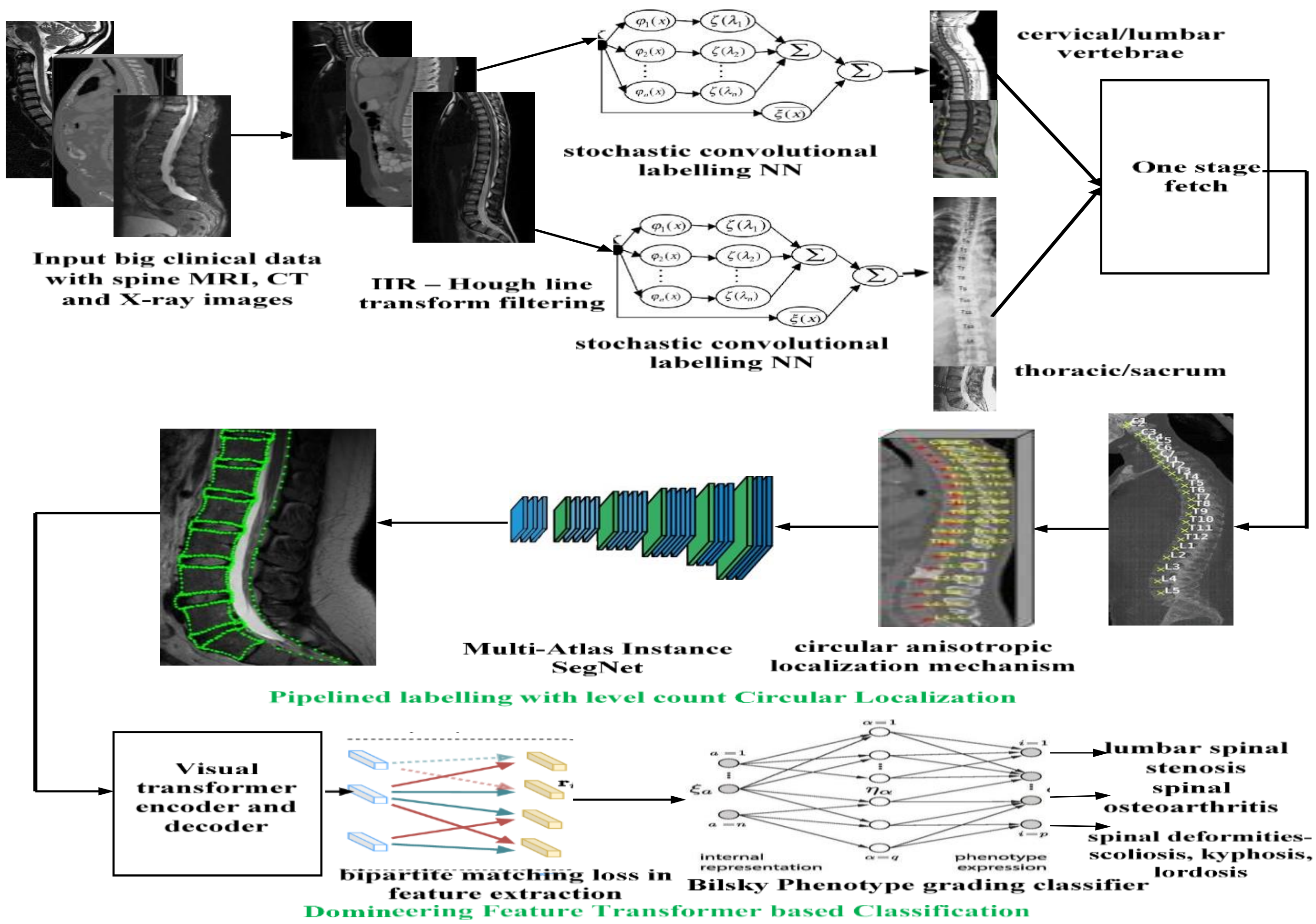

Fig. 1 Pipeline labelling based Classification Model

6. CONCLUSION AND FUTURE WORK

No research has been focused on big clinical data with diverse scanned images and the detection of multiple spinal disorders which has been done for the first time in this research. Abnormalities due to additional/transitional vertebrae have been handled for the first time in the localization process. Domineering feature extraction and phenotype-based mapping in ML classification for the prediction of multiple spinal disorders sublevels has been done for the first time.

In future the above model is to be implemented and can able to meet state-of-art.

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