Original Article

Investigation on Efficient Deep Learning Framework for Spinal Deformities: A Review Approach

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Abstract

The present paper is related to the survey on the Investigation on Efficient Deep Learning Framework for Sipal Deformities. In this paper, some selected papers are taken for the investigation to find research gaps or extensions of existing research in the selected domain. The central nervous system is the most significant processing unit in the human body, and it is located in the central nervous system. Management and control of all the key organs from head to toe including eye blinking, breathing, heart pumping and movement of motion including bending and twisting are all managed and controlled by this system. The central nervous system is comprised of two primary organs: the brain, which is the most important, and the spinal cord, which is the second most important. The brain stem serves as the spinal column's beginning point. In its most basic form, the spinal cord is a delicate vertical pipe with a solid texture that includes a collection of nerves and tissues.

Keywords- Efficient Deep Learning, Spinal Cord, Spinal Deformities, Central Nervous System, Management & Control.

I.INTRODUCTION

1.1 Central Nervous System

It is the most significant processing unit in the human body, and it is located in the central nervous system. Management and control of all the key organs from head to toe including eye blinking, breathing, heart pumping and movement of motion including bending and twisting are all managed and controlled by this system. The central nervous system is comprised of two primary organs: the brain, which is the most important, and the spinal cord, which is the second most important. The brain stem serves as the spinal column's beginning point. In its most basic form, the spinal cord is a delicate vertical pipe with a solid texture that includes a collection of nerves and tissues.

The nervous system is a critical component of the human body. One of the most important organs in the body, the spinal cord, and explaining its importance are critical job. Damage to a critical node in the information transmission network might have ramifications for the functioning of any other key organ in the body. Information signals are sent to different regions of the body via the spine nerves, which work in conjunction with sensory signals. They serve as the primary communication mechanism for the human body since they link each organ and its reaction to the central nervous system. The spinal cord helps the brain, which serves as the information processing unit, to receive and transmit all of the information. The spine contributes to the overall movement of the body. Figure 1 shows the spinal cord five regions.

1.2 Spinal Posture Deformities

In addition to backache and weakness, frequent symptoms associated with spine disorders include loss of sensation (sweating and swelling), loss of bladder control, reflex action
(paralysis), and paralysis (paralysis). The clinical professional

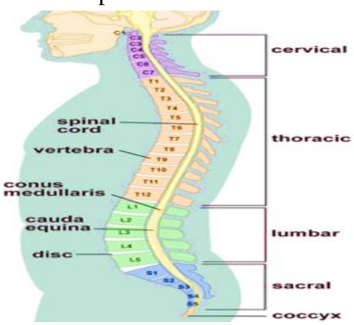

Figure 1. Spinal Five Regions

can determine who is afflicted by taking these symptoms into consideration. Infections, trauma injuries, vascular blockages, bone fractures, and tumors are all possible causes of these complications. The deformity of the spine is split into three categories as follows:

A. Scoliosis
Scoliosis is a kind of sideways curvature deformity of the spine that happens often during development and manifests itself just before puberty. It is one of the most common abnormalities of the spine that occurs during growth and manifests itself just before puberty. The majority of the time, incidences of scoliosis are moderate; nevertheless, as a kid develops, the abnormalities of the spine get more severe as well. Scoliosis is a condition that may result in impairment depending on its severity. Extreme curvature abnormalities, in particular, restrict the amount of space available in the chest, resulting in breathing difficulties as well as impairment of the function of the lungs and heart. The most typical signs of this instance are chronic back discomfort, as well as unequal shoulders, hips, and waistlines. Figure 2. (a) shows the Scoliosis.

B. Kyphosis
Kyphosis is defined as an excessive rounding of the back from the cervical area. Figure 2. (d) shows the Kyphosis. Simply put, it is a wedge-shaped malformation of the vertebrae that extend from the neck to the shoulder. Despite the fact that kyphosis may develop at any age, even in babies, it is more frequent in elderly women. There are three types of kyphosis:
1. Postural
2. Scheuermann
3. Congenital

C. Lordosis
Lordosis is a condition in which the lower lumber pelvic curvature, which is located above the buttocks, arches inwards excessively. Lordosis may result in excessive pressure being placed on the spine's structure, resulting in extreme pain and suffering, as well as impairing the subject's ability to move. Figure 2. (e) shows the Lordosis.

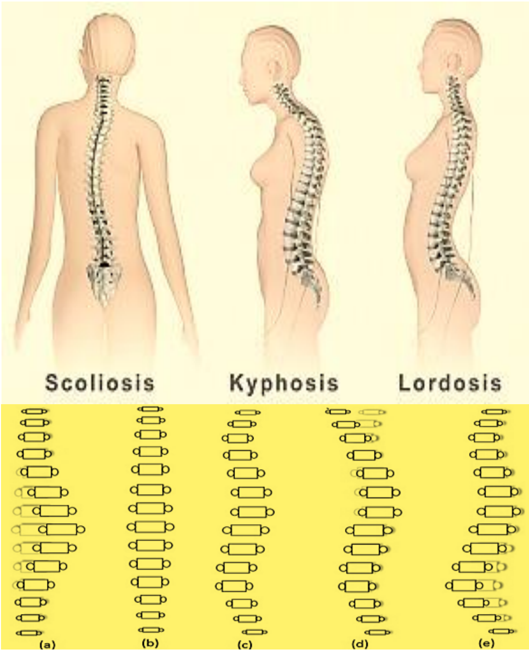

Figure 2. Spine abnormalities: (a) Scoliosis (b) Normal front view (c) Normal side view (d) Kyphosis (e) Lordosis

1.3 Radiological Diagnosis
A variety of imaging techniques are available for the examination and diagnosis of disorders related to spine position. Radiography pictures are the most well-known and least expensive of any. With the advancement of technology in the field of deep study analysis, a variety of alternatives are now accessible, including the following:

A. X-ray Images
Wilhelm Conrad Roentgen made the groundbreaking discovery of X-ray imaging technology in 1895. The inside structure of the body may be captured and seen using x-rays, which are electromagnetic waves-based radiations. The bombardment of radiation to the body, and the calcium content of bone substance, naturally absorb these radiations, resulting in a dazzling white structure on film when photographed. Radiology imaging of the spinal cord is a highly common and inexpensive approach to diagnosing the condition. X-ray image analysis aids in the detection of any spine disorders such as fractures, tumors, and problems with the vertebral column. Figure 3 shows the X-ray Radiography.

Figure 3. X-ray Radiograph

B. Computed Tomography (CT) Scan

Godfrey Hounsfield of EMI Laboratories, a British scientist who worked in the early 1970s, invented computed tomography (CT) technology. For the investigation and diagnosis of spinal diseases, it is another imaging modality to consider. A composite picture is just a collection of enhanced X-ray images taken from various angles and orientations. These scans are processed with the use of measuring parameters, and the results are cross-sectional pictures of an organ taken from various angles. CT scans are being used to create 3D models of the spinal cord, which may be used to diagnose and treat patients. The clinical professional may examine the model at all scales and orientation changes, depending on his or her preference. Figure 4. shows the CT Scan Radiography.

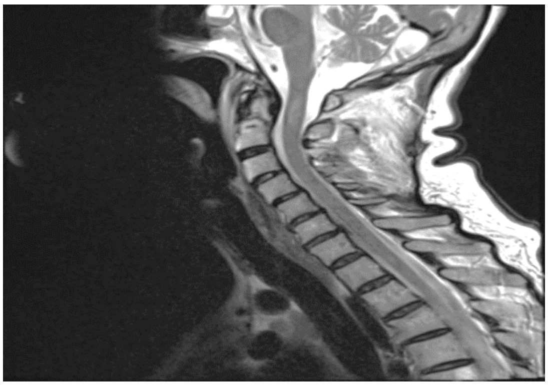

Figure 4. CT Scan Radiograph

C. Magnetic Resonance Imaging (MRI) Scans

When it comes to the radiological examination of the spinal cord, magnetic resonance imaging (MRI) is a high-quality and thorough technique. This non-invasive imaging approach creates pictures by using a high magnetic field and radiofrequency pulses to create images on a computer screen. Felix Bloch and Edward Purcell developed magnetic resonance imaging (MRI) in 1946. Figure 5. shows the MRI Scan Radiography.

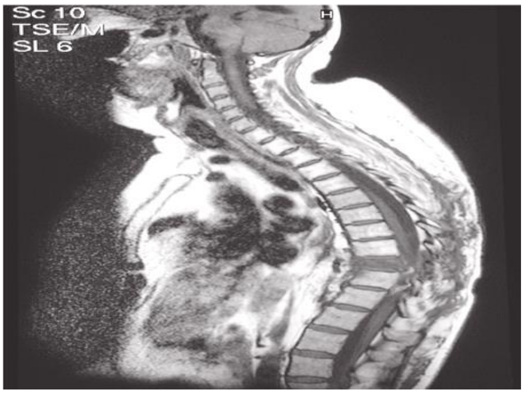

Figure 5. MRI Scan Radiograph

II. LITERATURE SURVEY

This paper examines and evaluates the published academic work that is linked to the use of Artificial Intelligence and Machine Learning Techniques in spinal surgery. The following articles are recommended for those who want to gain knowledge and grasp the most recent research in spinal surgery.

Alharbi, R. H., et al. (2020) [1]"proposed an automatic measurement algorithm with machine learning. Initially, X-Rays images are processed utilizing the CLAHE method. Then, deep convolutional neural networks (CNN) are applied to detect vertebrae in each X-Ray image. At last, the Cobb angle is measured through a novel algorithm using trigonometry. The proposed method is evaluated on the X-Rays dataset from King Saud University (KSU), and it detects each vertebra in those images. In addition, Cobb angle measurements are compared with experts' manual measurements. Their method achieves the estimation of Cobb angles with high accuracy, showing its great potential in clinical use".

Altini, N., et al. (2021) [2]"proposed a framework that addresses the tasks of vertebrae segmentation and identification by exploiting both deep learning and classical machine learning methodologies. The proposed solution comprises two phases: a binary fully automated segmentation of the whole spine, which exploits a 3D convolutional neural network, and a semi-automated procedure that allows locating vertebrae centroids using traditional machine learning algorithms. Unlike other approaches, the proposed method comes with the added advantage of no requirement for single vertebrae-level annotations to be trained. A dataset of 214 CT scans has been extracted from VerSe'20 challenge data, for training, validating and testing the proposed approach. In addition, to evaluate the robustness of the segmentation and labeling algorithms, 12 CT scans from subjects affected by severe, moderate and mild scoliosis have been collected from a local medical clinic. On the designated test set from Verse'20 data, the binary spine segmentation stage allowed to obtain a binary Dice coefficient of 89.17%, whilst the vertebrae identification one reached an average multi-class Dice coefficient of 90.09%. In order to ensure the reproducibility of the algorithms hereby developed, the code has been made publicly available".

André, A., et al. (2020) [3]"performed a retrospective study of complete Electronic Health Records (EHR) to identify potential unfavorable criteria for spine surgery (predictors). A cohort of synthetics EHR was created to classify patients by surgical success (green zone) or partial failure (orange zone) using an Artificial Neural Network which screens all the available predictors. In the actual cohort, they included 60 patients, with complete EHR allowing efficient analysis, 26 patients were in the orange zone (43.4%) and 34 were in the green zone (56.6%). The average positive criteria amount for actual patients was 8.62 for the green zone (SD+/- 3.09) and 10.92 for the orange zone (SD 3.38). The classifier (a neural network) was trained using 10,000 virtual patients and 2000 virtual patients were used for test purposes. The 12,000 virtual patients were generated from the 60 EHR, of which half were in the green zone and half in the orange zone. The model showed an accuracy of 72% and a ROC score of 0.78. The sensitivity was 0.885 and the specificity 0.59. Their method can be used to predict a favorable patient to have lumbar decompression surgery. However, there is still a need to further develop its ability to analyze patients in the "failure of treatment" zone to offer precise management of patient health before spinal surgery".

Azad, T. D., et al. (2021) [4]"attempted to characterize methods to improve reproducibility and to allow for better clinical performance, utilize they a previously proposed taxonomy that separates reproducibility into 3 components: technical, statistical, and conceptual reproducibility. By following this framework, they discuss common errors that lead to poor reproducibility, highlight the importance of generalizability when evaluating a ML model's performance, and provide suggestions to optimize generalizability to ensure adequate performance. These efforts are a necessity before such models are applied to patient care".

Bhatkoti, P., & Paul, M. (2016) [5]"used a deep learning framework with modified k-sparse autoencoder (σKSA) classification to locate neutrally degenerated areas of the brain magnetic resonance imaging (MRI), low amyloid-beta 1-42 imaging in cerebrospinal fluid (CSF), and positron emission tomography (PET) imaging of amyloid; each with a sample of 150 images. Results show a correlation between computational demarcation of infected regions and the images. Degeneration in the studied areas was evidenced by high phosphorylated t-/p-tau levels in CSF, regional fluorodeoxyglucose PET, and the presence of atrophy patterns. The use of the σKSA algorithm in boosting classification helped to improve the classifier performance. The KSA method with a deep learning framework is used for the first time to produce accurate results in the diagnosis of Alzheimer's disease".

Bidabadi, S. S., et al. (2019) [6]"examined if it is feasible to use commercial off-the-shelf Inertial measurement unit sensors and supervised learning methods to distinguish foot drop gait disorder from the normal walking gait pattern.The gait data collected from 56 adults diagnosed with foot drop due to L5 lumbar radiculopathy (with MRI verified compressive pathology), and 30 adults with normal gait during multiple walking trials on a flat surface. Machine learning algorithms were applied to the inertial sensor data to investigate the feasibility of classifying foot drop disorder. The best three performing results were 88.45%, 86.87% and 86.08% accuracy derived from the Random Forest, SVM, and Naive Bayes classifiers respectively. After applying the wrapper feature selection technique, the top performance was from the Random Forest classifier with an overall accuracy of 93.18%. It is demonstrated that the combination of inertial sensors and machine learning algorithms, provides a promising and feasible solution to differentiating L5 radiculopathy related foot drop from normal walking gait patterns. The implication of this finding is to provide an objective method to help clinical decision making".

Buchlak, Q. D., et al. (2020) [7]"assessed the current state of neurosurgical ML applications and the performance of algorithms applied. Their systematic search strategy yielded 6866 results, 70 of which met inclusion criteria. Performance statistics analyzed included area under the receiver operating characteristics curve (AUC), accuracy, sensitivity, and specificity. Natural language processing (NLP) was used to model topics across the corpus and to identify keywords within surgical subspecialties. ML applications were heterogeneous. The densest cluster of studies focused on preoperative evaluation, planning, and outcome prediction in spine surgery. The main algorithms applied were NN, LR, and SVM. Input and output features varied widely and were listed to facilitate future research. The accuracy ($F(2,19) = 6.56$, $p < 0.01$) and specificity ($F(2,16) = 5.57$, $p < 0.01$) of NN, LR, and SVM differed significantly. NN algorithms demonstrated significantly higher accuracy than LR. SVM demonstrated significantly higher specificity than LR. They found no significant difference between NN, LR, and SVM AUC and sensitivity. NLP topic modeling reached maximum coherence at seven topics, which were defined by modeling approach, surgery type, and pathology themes. Keywords captured research foci within surgical domains. ML technology accurately predicts outcomes and facilitates clinical decision-making in neurosurgery. NNs frequently outperformed other algorithms on supervised learning tasks. Their study identified gaps in the literature and opportunities for future neurosurgical ML research".

Chae, D. S., et al. (2020) [8]"presented an automated method for precisely measuring spinopelvic parameters using a decentralized convolutional neural network as an efficient replacement for the current manual process which not only requires experienced surgeons but also shows limitations in the ability to process large numbers of images to accommodate the explosion of big data technologies. The proposed method is based on gradually narrowing the regions of interest (ROIs) for feature extraction and leads the model to mainly focus on the necessary geometry characteristics represented as key points. According to key points obtained, parameters representing the spinal deformity are calculated, which consistency with manual measurement was validated by 40 test cases and, potentially, provided 1.45^0 mean absolute values of deviation for PTA as the minimum and 3.51^0 in case of LSA as maximum".

Chang, M., et al. (2020) [9]"introduced the overall field of machine learning and its role in artificial intelligence, and defines basic terminology. In addition, common modalities for applying machine learning, including classification and regression decision trees, support vector machines, and artificial neural networks are examined in the context of examples gathered from the spine literature. Lastly, the ethical challenges associated with adapting machine learning for research related to patient care, as well as future perspectives on the potential use of machine learning in spine surgery, are discussed specifically".

Chen, H., et al. (2015) [10]"presented a robust and efficient approach to automatically locating and identifying vertebrae in 3D CT volumes by exploiting high-level feature representations with a deep convolutional neural network (CNN). A novel joint learning model with CNN (J-CNN) is proposed by considering both the appearance of vertebrae and the pairwise conditional dependency of neighboring vertebrae. The J-CNN can effectively identify the type of vertebra and eliminate false detections based on a set of coarse vertebral centroids generated from a random forest classifier. Furthermore, the predicted centroids are refined by a shape regression model. Their approach was quantitatively evaluated on the dataset of MICCAI 2014 Computational Challenge on Vertebrae Localization and Identification. Compared with the state-of-the-art method, our approach achieved a large margin with a 10.12% improvement in the identification rate and smaller localization errors".

Cho, B. H., et al. (2020) [11]"developed a segmentation neural network (n = 629). After synthetic augmentation, 70% of these radiographs were used for network training, while the remaining 30% were used for hyperparameter optimization. A computer vision algorithm was deployed on the segmented radiographs to calculate lumbar lordosis angles. A test set of radiographs was used to evaluate the validity of the entire pipeline (n = 151).The U-Net segmentation achieved a test dataset dice score of 0.821, an area under the receiver operating curve of 0.914, and an accuracy of 0.862. The computer vision algorithm identified the L1 and S1 vertebrae on 84.1% of the test set with an average speed of 0.14 seconds/radiograph. From the 151 test set radiographs, 50 were randomly chosen for surgeon measurement. When compared with those measurements, our algorithm achieved a mean absolute error of 8.055° and a median absolute error of 6.965° (not statistically significant, $P > .05$). This study is the first to use artificial intelligence and computer vision in a combined pipeline to rapidly measure a sagittal spinopelvic parameter without prior manual surgeon input. The pipeline measures angle with no statistically significant differences from manual measurements by surgeons. This pipeline offers clinical utility in an assistive capacity, and future work should focus on improving segmentation network performance".

Cho, J. S., et al. (2018) [12]"discussed the application of a machine learning approach (Support vector machine, SVM) for the automatic cognition of gait changes due to scoliosis using gait measures: kinematic based on gait phase segmentation. The gaits of 18 controls and 24 scoliosis patients were recorded and analyzed using inertial measurement unit (IMU)-based systems during normal walking. Altogether, 72 gait features were extracted for developing gait recognition models. Cross-validation test results indicated that the performance of SVM was 90.5% to recognize scoliosis patients and controls gait patterns. When features were optimally selected, a feature selection algorithm could effectively distinguish the age groups with 95.2% accuracy. Applying the method that the previous test used, the severity of scoliosis was classified after clinician labeled the severity based on the Cobb angle. Test results indicated an accuracy of 81.0% by the SVM to recognize scoliosis severity gait patterns. Optimal selected features could effectively distinguish the scoliosis severity with 85.7% accuracy. When the measured features are ranked in order of high contribution, the abduction and adduction of left hip joint in the single support phase is most important in gait of patients with scoliosis. These results demonstrate considerable potential in applying SVMs in gait classification for medical applications".

Dhillon, A., & Singh, A. (2019) [13]"described different types of machine learning algorithms. Then use of machine learning algorithms for analyzing various healthcare data are surveyed".

Furqan Qadri, S., et al. (2018) [14]"proposed a deep learning approach for automatic CT vertebra segmentation named patch-based deep belief networks (PaDBNs). Their proposed PaDBN model automatically selects the features from image patches and then measures the differences between classes and investigates performance. The region of interest (ROI) is obtained from CT images. Unsupervised feature reduction contrastive divergence algorithm is applied for weight initialization, and the weights are optimized by layers in a supervised fine-tuning procedure. The discriminative learning features obtained from the steps above are used as input of a classifier to obtain the likelihood of the vertebrae. Experimental results demonstrate that the proposed PaDBN model can considerably reduce computational cost and produce an excellent performance in vertebra segmentation in terms of accuracy compared with state-of-the-art methods".

Galbusera, F., et al. (2019) [15]"presented a brief description of the various techniques that are being developed nowadays, with special focus on those used in spine research. Then, they describe the applications of AI and ML to problems related to the spine which have been published so far, including the localization of vertebrae and discs in radiological images, image segmentation, computer-aided diagnosis, prediction of clinical outcomes and complications, decision support systems, content-based image retrieval, biomechanics, and motion analysis. Finally, they briefly discuss major ethical issues related to the use of AI in healthcare, namely, accountability, risk of biased decisions as well as data privacy and security, which are nowadays being debated in the scientific community and by regulatory agencies".

Galbusera, F., et al. (2020) [16]"trained a deep neural network for the three-dimensional estimation of the direction of the three anatomical axes (craniocaudal, anteroposterior, and laterolateral) of individual vertebrae from a single sagittal radiographic image acquired from an approximately lateral direction with large deviations from a perfect alignment up to 60 degrees. To this aim, we exploited computed tomography (CT), which can be used to create simulated radiographic projections with different orientations, for the creation of large training and validation datasets. In a set of 21 CT stacks, the location of 5 landmark points was manually determined for L2, L3, and L4, for a total of 63 vertebrae. For each vertebra, 200 simulated projections were approximately aligned with the sagittal plane but including random perturbations of the projection, the direction was built, resulting in 12,600 simulated radiographs with the corresponding local directions of the anatomical axes. These data were integrated by 1765 lateral images of vertebrae acquired with a biplanar radiographic imaging system, for which the orientation was calculated by means of three-dimensional reconstruction. The whole dataset was used to train a deep neural network, ResNet-101, customized for the estimation of the three-dimensional components of the axes. The accuracy of the network was qualitatively and quantitatively tested on a large group of simulated radiographic images as well as real lateral images acquired with a biplanar radiographic system for which the direction of the axes was known. Errors were lower than 3 degrees in 76% of the evaluations conducted on the simulated images, and in 86% for the real radiographs. The novel method will be useful to extract three-dimensional information from planar images even in clinical cases in which vertebrae are markedly rotated due to spinal deformities or to an imprecise alignment of the patient with respect to the detector".

Ghogawala, Z., et al. (2019) [17]"examined how clinical registries might be used to generate new evidence to support a particular treatment option when comparable options exist. Lumbar spondylolisthesis is used as an example. They reviewed the literature examining the comparative effectiveness of decompression alone versus decompression with fusion for lumbar stenosis with degenerative spondylolisthesis. Modern data acquisition for the creation of registries was also reviewed with an eye to how artificial intelligence for the treatment of lumbar spondylolisthesis might be explored. Current randomized controlled trials differ on the importance of adding fusion when performing decompression for lumbar spondylolisthesis. Standardized approaches to extracting data from the electronic medical record as well as the ability to capture radiographic imaging and incorporate patient-reported outcomes (PROs) will ultimately lead to the development of modern, structured, data-filled registries that will lay the foundation for machine learning.There is a growing realization that patient experience, satisfaction, and outcomes are essential to improving the overall quality of spine care. There is a need to use practical, validated PRO tools in the quest to optimize outcomes within spine care. Registries will be designed to contain robust clinical data in which predictive analytics can be generated to develop and guide data-driven personalized spine care".

Han, Z., Wei, B., et al. (2018) [18]"combined deep learning and symbolic program synthesis theory to overcome four inevitable tasks: semantic segmentation, radiological classification, positional labeling, and structural captioning. The weakly supervised framework using object level annotations without requiring radiologist-level report annotations to generate unified reports. Each generated report covers almost type lumbar structures comprised of six intervertebral discs, six neural foramina, and five lumbar vertebrae. The contents of each report contain the exact locations and pathological correlations of these lumbar structures as well as their normalities in terms of three type relevant spinal diseases: intervertebral disc degeneration, neural foraminal stenosis, and lumbar vertebrae deformities. This framework is applied to a large corpus of T1/T2-weighted sagittal MRIs of 253 subjects acquired from multiple vendors. Extensive experiments demonstrate that the framework is able to generate unified radiological reports, which reveals its effectiveness and potential as a clinical tool to relieve spinal radiologists from laborious workloads to a certain extent, such that contributes to relevant time savings and expedites the initiation of many specific therapies".

Jain, D., et al. (2020) [19]"created comprehensive models to predict discharge to facility, 90-day readmissions, and 90-day major medical complications after LSLPSF. This information can be used to guide decision making between the surgeon and patient, as well as inform value-based payment models".

Jayatilake, S. M. D. A. C., & Ganegoda, G. U. (2021)[20]"discussed various machine learning algorithms and approaches that are being used for decision making in the healthcare sector along with the involvement of machine learning in healthcare applications in the current context. With the explored knowledge, it was evident that neural network-based deep learning methods have performed extremely well in the field of computational biology with the support of the high processing power of modern sophisticated computers and are being extensively applied because of their high predicting accuracy and reliability. When giving concern towards the big picture by combining the observations, it is noticeable that computational biology and biomedicine-based decision making in healthcare have now become dependent on machine learning algorithms, and thus they cannot be separated from the field of artificial intelligence".

Kadoury, S., et al. (2017)[21]"introduced a novel approach for predicting the progression of adolescent idiopathic scoliosis from 3-D spine models reconstructed from biplanar X-ray images. Recent progress in machine learning has allowed to improve classification and prognosis rates but lacks a probabilistic framework to measure uncertainty in the data. They propose a discriminative probabilistic manifold embedding where locally linear mappings transform data points from high-dimensional space to corresponding low-dimensional coordinates. A discriminant adjacency matrix is constructed to maximize the separation between progressive (P) and nonprogressive (NP) groups of patients diagnosed with scoliosis while minimizing the distance in latent variables belonging to the same class. To predict the evolution of deformation, a baseline reconstruction is projected onto the manifold, from which a spatiotemporal regression model is built from parallel transport curves inferred from neighboring exemplars. The rate of progression is modulated from the spine flexibility and curve magnitude of the 3-D spine deformation. The method was tested on 745 reconstructions from 133 subjects using longitudinal 3-D reconstructions of the spine, with results demonstrating the discriminatory framework can identify between P and NP of scoliotic patients with a classification rate of 81% and the prediction differences of 2.1^0 in the main curve angulation, outperforming other manifold learning methods. Their method achieved a higher prediction accuracy and improved the modeling of spatiotemporal morphological changes in highly deformed spines compared with other learning methods".

Kamiya, N., et al. (2018) [22]"realized automatic recognition of the ESMs and its attachment region on the skeleton using a 2D deep convolutional neural network. Each cross section of the 3D computed tomography (CT) image is input as a 2D image to the fully convolutional network. Then, the obtained result is reconstructed into a 3D image to obtain the recognition result of the ESM and its attachment region on the skeleton. ESM and attached area are extracted manually from the CT images of 11 cases and used for evaluation. In the experiments, automatic recognition was performed for each case using the leave-one-out method. The mean recognition accuracy of ESM and attached area was 89.9% and 65.5%, respectively for the Dice coefficient. In this study, although there is over-extraction in the recognition of the attachment region, the initial region has been acquired successfully and it is the first study to simultaneously recognize the ESMs and its attachment region on the skeleton".

Korez, R., et al. (2020)[23]"evaluated the performance of a novel deep learning (DL) tool for fully automated measurements of the sagittal spinopelvic balance from X-ray images of the spine in comparison with manual measurements. Ninety-seven conventional upright sagittal X-ray images from 55 subjects were retrospectively included in this study. Measurements of the parameters of the sagittal spinopelvic balance, i.e., the sacral slope (SS), pelvic tilt (PT), spinal tilt (ST), pelvic incidence (PI), and spinosacral angle (SSA), were obtained manually by identifying specific anatomical landmarks using the SurgiMap Spine software and by the fully automated DL tool. Statistical analysis was performed in terms of the mean absolute difference (MAD), standard deviation (SD), and Pearson correlation, while the paired t-test was used to search for statistically significant differences between manual and automated measurements.The differences between reference manual measurements and those obtained automatically by the DL tool were, respectively, for SS, PT, ST, PI, and SSA, equal to 5.0° (3.4°), 2.7° (2.5°), 1.2° (1.2°), 5.5° (4.2°) and 5.0° (3.5°) in terms of MAD (SD), with a statistically significant corresponding Pearson correlation of 0.73, 0.90, 0.95, 0.81 and 0.71. No statistically significant differences were observed between the two types of measurement (p-value always above 0.05). The differences between measurements are in the range of the observer variability of manual measurements, indicating that the DL tool can provide clinically equivalent measurements in terms of accuracy but superior measurements in terms of cost-effectiveness, reliability, and reproducibility".

Krishnaraj, A., et al. (2019) [24]"presented algorithm can identify osteoporosis and osteopenia with a high degree of accuracy (82%) and a small proportion of false positives. Efforts to cull greater information using machine-learning algorithms from pre-existing data have the potential to have a marked impact on population health efforts such as bone mineral density screening for osteoporosis, in which gaps in screening currently exist".

Kulkarni, K. R., et al. (2017) [25]"studied the Lower back pain (LBP) is caused because of assorted reasons involving body parts such as the interconnected network of spinal cord, nerves, bones, discs or tendons in the lumbar spine. LBP is pain, muscle pressure, or stiffness localized underneath the costal edge or more the substandard gluteal folds, with or without leg torment for the most part sciatica, and is characterized as endless when it holds on for 12 weeks or more then again, non-particular LBP is torment not credited to an unmistakable pathology such as infection, tumour, osteoporosis, rheumatoid arthritis, fracture, or inflammation. Over 70% of people usually suffer from such backpain disorder at some time. But recovery is not always favorable, 82% of non-recent-onset patients still experience pain 1 year later. Even though not having any history of lower back pain, many patients suffering from this disorder spend months or years healing from it. Hence aiming to look for preventive measure rather than curative, their study suggests a classification methodology for Chronic LBP disorder using Deep Learning techniques".

Liu, T., Yang, Y., et al. (2020) [26]"designed a multi-scale keypoint estimation approach that incorporates Squeeze-and-Excitation(SE) blocks to improve the representational capacity of the model, achieving the assessment of spinal curve without large-size dataset. The proposed approach uses pose estimation framework to detect keypoints of spine with simple annotation and small-size dataset for the first time. Finally, they conduct experiments on a collected clinical dataset, and results illustrate that our approach outperforms the mainstream approaches".

Löffler, M. T., et al. (2020) [27]"provided vertebral segmentation masks for spine CT images and annotations of vertebral fractures or abnormalities per vertebral level; it is available from https://osf.io/nqjyw/ and is intended for large-scale machine learning aimed at automated spine processing and fracture detection.This public CT dataset holds 160 image series of 141 patients including segmentation masks of 1725 fully visualized vertebrae; it is split into a training dataset (80 image series, 862 vertebrae), a public validation dataset (40 image series, 434 vertebrae), and a secret test dataset (40 image series, 429 vertebrae, to be released in December 2020). Metadata includes annotations of vertebral fractures using the semiquantitative method by Genant and of instances of foreign material per vertebral level, as well as opportunistic measurements of lumbar bone mineral density per patient. This dataset was prepared for a vertebral labeling and segmentation challenge hosted at the 2019 International Conference on Medical Image Computing and Computer-Assisted Intervention".

Mallow, G. M., et al. (2021) [28]"developed the building blocks of the IBSC model and perfected, and several have already brought technological innovation to other specialties. It's not a question of "if," but "when" AI will meaningfully connect these platforms to form a coherent IBSC that will, with the utmost precision, guide the treatment of various spine pathologies. However, before a recognizable IBSC model can take shape, research needs to be directed at integrating the various components of the IBSC model, and ML and DL models need to be validated across global regions to ensure efficacy across ethnically diverse populations. Moreover, data sharing and access to large datasets that promote collaboration and consortia need to be established. Additionally, a framework for maintaining and retraining models needs to be instituted to avoid model drift, or the degradation of prediction accuracy over time, as the mapping of historical observations to future outcomes is not static. As these challenges are surmounted and each platform interlinked, the IBSC model is sure to one day be highly impactful in the world of spine care, possibly even reducing years spent living with debilitating spine disorders and minimizing the financial burden that such conditions have on our healthcare systems".

Mbarki, W., et al. (2020) [29]"interested in convolutional neural networks (CNN); it was characterized by a topology similar to a visual cortex of mammals. In fact, these kind of techniques has been applied successfully in many classification problems. In order to recognize herniated lumbar disc in Magnetic Resonance Imaging (MRI), they have chosen to use Convolutional neural networks based on VGG16 architecture. Experiments were carried on their own dataset from Sahloul University Hospital of Sousse. The accuracy achieved of the trained model was 94% which represents high-performance results by providing state of the art. Their system is very efficient and effective for detecting and diagnosing herniated lumbar disc. Therefore, the contribution of their study includes in: Firstly, the using of the U-net deep neural network architecture to localize and to detail the location of the herniation. Secondly, the using of the axial view MRI in order to locate exactly the pathological and the normal intervertebral discs. The main objective of their work was to help radiologists in diagnosing and treating lumbar herniated disc disease".

Merali, Z. A., Colak, E., & Wilson, J. R. (2021) [30]"perfomed a literature search utilizing the PubMed database. Relevant studies from all the evidence levels have been included.Within spine surgery, artificial intelligence and machine learning technologies have achieved near-human performance in narrow image classification tasks on specific datasets in spinal degenerative disease, spinal deformity, spine trauma, and spine oncology.Although substantial challenges remain to be overcome it is clear that artificial intelligence and machine learning technology will influence the practice of spine surgery in the future".

Mushtaq, M., et al. (2022) [31]"presented the methods that will help clinicians to grade the severity of the disease with confidence, as the current manual diagnosis by different doctors has dissimilarity and variations in the analysis of diseases. They discussed the lumbar spine localization and segmentation which help for the analysis of lumbar spine deformities. The lumber spine is localized using YOLOv5 which is the fifth variant of the YOLO family. It is the fastest and the lightest object detector. Mean average precision (mAP) of 0.975 is achieved by YOLOv5. To diagnose the lumbar lordosis, we correlated the angles with region area that is computed from the YOLOv5 centroids and obtained 74.5% accuracy. Cropped images from YOLOv5 bounding boxes are passed through HED U-Net, which is a combination of segmentation and edge detection frameworks, to obtain the segmented vertebrae and its edges. Lumbar lordortic angles (LLAs) and lumbosacral angles (LSAs) are found after detecting the corners of vertebrae using a Harris corner detector with very small mean errors of 0.29° and 0.38°, respectively. Theycompare the different object detectors used to localize the vertebrae, the results of two methods used to diagnose the lumbar deformity, and the results with other researchers".

Nguyen, H. T., et al. (2021) [32]"developed and evaluated a deep learning-based framework, named VinDr-SpineXR, for the classification and localization of abnormalities from spine X-rays. First, they build a large dataset, comprising 10,468 spine X-ray images from 5,000 studies, each of which is manually annotated by an experienced radiologist with bounding boxes around abnormal findings in 13 categories. Using this dataset, we then train a deep learning classifier to determine whether a spine scan is abnormal and a detector to localize 7 crucial findings amongst the total 13. The VinDr-SpineXR is evaluated on a test set of 2,078 images from 1,000 studies, which is kept separate from the training set. It demonstrates an area under the receiver operating characteristic curve (AUROC) of 88.61% (95% CI 87.19%, 90.02%) for the image-level classification task and a mean average precision (mAP@0.5) of 33.56% for the lesion-level localization task. These results serve as a proof of concept and set a baseline for future research in this direction. To encourage advances, the dataset, codes, and trained deep learning models are made publicly available".

Rehman, F., et al. (2020) [33]"presented a novel combination of traditional region-based level set with deep learning framework in order to predict shape of vertebral bones accurately; thus, it would be able to handle the fractured cases efficiently. They termed this novel Framework as "FU-Net" which is a powerful and practical framework to handle fractured vertebrae segmentation efficiently. The proposed method was successfully evaluated on two different challenging datasets: (1) 20 CT scans, 15 healthy cases, and 5 fractured cases provided at spine segmentation challenge CSI 2014; (2) 25 CT image data (both healthy and fractured cases) provided at spine segmentation challenge CSI 2016 or xVertSeg.v1 challenge. They have achieved promising results on their proposed technique especially on fractured cases. Dice score was found to be $96.4 \pm 0.8\%$ without fractured cases and $92.8 \pm 1.9\%$ with fractured cases in CSI 2014 dataset (lumber and thoracic). Similarly, dice score was $95.2 \pm 1.9\%$ on 15 CT dataset (with given ground truths) and $95.4 \pm 2.1\%$ on total 25 CT dataset for CSI 2016 datasets (with 10 annotated CT datasets). The proposed technique outperformed other state-of-the-art techniques and handled the fractured cases for the first time efficiently".

Saravi, B., et al. (2022) [34]"focused on key advances in machine and deep learning, allowing for multi-perspective pattern recognition across the entire information set of patients in spine surgery. This is the first review of artificial intelligence focusing on hybrid models for deep learning applications in spine surgery, to the best of our knowledge. This is especially interesting as future tools are unlikely to use solely one data modality. The techniques discussed could become important in establishing a new approach to decision-making in spine surgery based on three fundamental pillars: (1) patient-specific, (2) artificial intelligence-driven, (3) integrating multimodal data. The findings reveal promising research that already took place to develop multi-input mixed-data hybrid decision-supporting models. Their implementation in spine surgery may hence be only a matter of time".

Schwartz, J. T., et al. (2019)[35]"examined the current state of machine learning using electronic medical records as it applies to spine surgery. Studies across the electronic medical record data domains of imaging, text, and structured data are reviewed. Discussed applications include clinical prognostication, preoperative planning, diagnostics, and dynamic clinical assistance, among others. The limitations and future challenges for machine learning research using electronic medical records are also discussed".

Sekuboyina, A., et al. (2017) [36]"proposed a novel deep learning-based method for segmenting the spine, which does not rely on any pre-defined shape model. They employ two networks: one for localisation and another for segmentation. Since a typical spine CT scan cannot be processed at once owing to its large dimensions, they find that both nets are essential to work towards a perfect segmentation. They evaluate their framework on three datasets containing healthy and fractured cases: two private and one public. Our approach achieves a mean Dice coefficient of ∼0.87, which is comparable but not higher than the state-of-art model-based approaches. However, they show that our approach handles degenerate cases more accurately".

Suzani, A., et al. (2015)[37]"presented an automatic method for detection and localization of vertebrae in volumetric computed tomography (CT) scans. The method makes no assumptions about which section of the vertebral column is visible in the image. An efficient approach based on deep feed-forward neural networks is used to predict the location of each vertebra using its contextual information in the image. The method is evaluated on a public data set of 224 arbitrary-field-of-view CT scans of pathological cases and compared to two state-of-the-art methods. Their method can perform vertebrae detection at a rate of 96% with an overall run time of less than 3 seconds. Its fast and comparably accurate detection makes it appealing for clinical diagnosis and therapy applications".

Tajdari, M., et al. (2021)[38]"proposed a mechanistic machine learning algorithm in order to study patient-specific AIS curve progression, which is associated with bone growth and other genetic and environmental factors. Two different frameworks are used to analyse and predict curve progression, one with implementing clinical data extracted from 2D X-ray images and the other one with incorporating both clinical data and physical equations governing the non-uniform bone growth. The physical equations governing bone growth are affiliated with calculating all stress components at each region. The stress values are evaluated through a surrogate finite element simulation and a bone growth model on a detailed patient-specific geometry of the human spine. They proposed a patient-specific framework to generate the volumetric model of the human spine which is partitioned into different tissues for both vertebra and intervertebral disc. It is shown that implementing physical equations governing bone growth into the prediction framework will notably improve the prediction results as compared to only using clinical data for prediction. In addition, they can predict curve progression at ages outside the range of training samples".

Tomita, N., et al. (2018)[39]"presented and evaluated an automatic system that can detect incidental OVFs in chest, abdomen, and pelvis CT examinations at the level of practicing radiologists. Their OVF detection system leverages a deep convolutional neural network (CNN) to extract radiological features from each slice in a CT scan. These extracted features are processed through a feature aggregation module to make the final diagnosis for the full CT scan. They explored different methods for this feature aggregation, including the use of a long short-term memory (LSTM) network. They trained and evaluated our system on 1432 CT scans, comprised of 10,546 two-dimensional (2D) images in sagittal view. Their system achieved an accuracy of 89.2% and an F1 score of 90.8% based on our evaluation on a held-out test set of 129 CT scans, which were established as reference standards through standard semiquantitative and quantitative methods. The results of their system matched the performance of practicing radiologists on this test set in real-world clinical circumstances. They expect the proposed system will assist and improve OVF diagnosis in clinical settings by pre-screening routine CT examinations and flagging suspicious cases prior to review by radiologists".

Tu, Y., Wang, N., Tong, F., & Chen, H. (2019)[40]"proposed a deep learning-based scoliosis Cobb angle measurement algorithm that can automatically calculate Cobb angle without the physician's manual definition. A DU-Net detection and segmentation network is proposed to remove the unrelated regions and segment the spine contour in the spine X-ray image. The aggregated channel features in the pedestrian detection algorithm are introduced to scoliosis image to realize the spine region detection and the DU-Net network is training to segment spine contour. Therefore, the spine curve can be fitted by the spine contour and the Cobb angle can be automatically measured by the tangent line of the spine curve. As a result, the Cobb angle measure method yields an average error of 2.9° to reference the Cobb angle which is measured manually by a special orthopaedist. The detection algorithm in this paper yields an average precision of 98.5% and a recall of 99.5%. Moreover, the DU-Net reaches an average Dice coefficient to reference segmentation of 90.28%, an IOU of 82.29%, and a precision of 86.30%".

Vergari, C., Skalli, W., & Gajny, L. (2020) [41]"proposed classification model, the originality of which is the coupling of a CNN with discriminant analysis, can be used to automatically label radiographs for the presence of scoliosis treatment. This information is usually missing from DICOM metadata, so such a reach method could facilitate the use of large databases. Furthermore, the same model architecture could potentially be applied for other radiograph classifications, such as sex and the presence of scoliotic deformity".

Von Atzigen, et al. (2021) [42]"proposed a novel, markerless surgical navigation proof-of-concept to bending rod implants. Their method combines augmented reality with on-device machine learning to generate and display a virtual template of the optimal rod shape without touching the instrumented anatomy. Performance was evaluated on lumbosacral spine phantoms against a pointer-based navigation benchmark approach and ground truth data obtained from computed tomography. Their method achieved a mean error of 1.83 ± 1.10 mm compared to 1.87 ± 1.31 mm measured in the marker-market-based, while only requiring 21.33 ± 8.80 s as opposed to 36.65 ± 7.49 s attained by the pointer-based method. Their results suggest that the combination of augmented reality and machine learning has the potential to replace conventional pointer-based navigation in the future".

Watanabe, K., et al. (2019)[43]"created a scoliosis screening system that estimates spinal alignment, the Cobb angle, and vertebral rotation from moiré images. In our system, a convolutional neural network (CNN) estimates the positions of 12 thoracic and 5 lumbar vertebrae, 17 spinous processes, and the vertebral rotation angle of each vertebra. They used this information to estimate the Cobb angle. The mean absolute error (MAE) of the estimated vertebral positions was 3.6 pixels (~5.4 mm) per person. T1 and L5 had smaller MAEs than the other levels. The MAE per person between the Cobb angle measured by doctors and the estimated Cobb angle was 3.42°. The MAE was 4.38° in normal spines, 3.13° in spines with a slight deformity, and 2.74° in spines with a mild to severe deformity. The MAE of the angle of vertebral rotation was 2.9°±1.4°, and was smaller when the deformity was milder. The proposed method of estimating the Cobb angle and AVR from moiré images using a CNN is expected to enhance the accuracy of scoliosis screening".

Weber, K. A., et al. (2019) [44]"investigated the relationship between fat infiltration in the cervical multifidi and fat infiltration measured in the lower extremities to move further into understanding the complex signs and symptoms arising from whiplash trauma. Thirty-one individuals with chronic whiplash associated disorders, stratified into a mild/moderate group and a severe group, together with 31 age- and gender-matched controls were enrolled in this study. Magnetic resonance imaging was used to acquire a 3D volume of the neck and of the whole body. Cervical multifidi were used to represent muscles local to the whiplash trauma and all muscles below the hip joint, the lower extremities, were representing widespread muscles distal to the site of the trauma. The fat infiltration was determined by a fat fraction in the segmented images. There was a linear correlation between local and distal muscle fat infiltration ($p<0.001$, $r2 = 0.28$). The correlation remained significant when adjusting for age and WAD group ($p = 0.009$) as well as when correcting for age, WAD group, and BMI ($p = 0.002$). There was a correlation between local and distal muscle fat infiltration within the severe WAD group ($p = 0.0016$, $r2 = 0.69$) and in the healthy group ($p = 0.022$, $r2 = 0.17$) but not in the mild/moderate group ($p = 0.29$, $r2 = 0.06$). No significant differences ($p = 0.11$) in the lower extremities' MFI between the different groups were found. The absence of differences between the groups in terms of lower extremities' muscle fat infiltration indicates that, in this particular population, the whiplash trauma has a local effect on muscle fat infiltration rather than a generalized one".

Wirries, A., et al. (2021) [45]"showed thata 100% accurate prediction of an ODI range could be achieved by dividing the ODI scale into 12% sections. A maximum absolute difference of only 3.4% between individually predicted and actual ODI after 6 months of a given therapy was achieved with our most powerful model. The application of artificial intelligence as shown in this work also allowed to compare the actual patient values after 6 months with the prediction for the alternative therapy, showing deviations up to 18.8%. Deep learning in the supervised form applied here can identify patients at an early stage who would benefit from conservative therapy, and on the contrary, avoid painful and unnecessary delays for patients who would profit from surgical therapy. In addition, this approach can be used in many other areas of medicine as an effective tool for decision-making when choosing between opposing treatment options, despite small patient groups".

Yang, J., Zhang, K., et al. (2019) [46]"developed and validated deep learning algorithms for automated scoliosis screening using unclothed back images. The accuracies of the algorithms were superior to those of human specialists in detecting scoliosis, detecting cases with a curve ≥20°, and severity grading for both binary classifications and the four-class classification. Their approach can be potentially applied in routine scoliosis screening and periodic follow-ups of pretreatment cases without radiation exposure".

Yeh, Y. C., et al. (2021) [47]"developed deep learning models capable of automatically locating 45 anatomic landmarks and subsequently generating 18 radiographic parameters on a whole-spine lateral radiograph. In the assessment of model performance, the localisation accuracy and learning speed were the highest for landmarks in the cervical area, followed by those in the lumbosacral, thoracic, and femoral areas. All the predicted radiographic parameters were significantly correlated with ground truth values (all $p < 0.001$). The human and artificial intelligence comparison revealed that the deep learning model was capable of matching the reliability of doctors for 15/18 of the parameters. The proposed automatic alignment analysis system was able to localise spinal anatomic landmarks with high accuracy and to generate various radiographic parameters with favourable correlations with manual measurements".

Zhang, B., et al. (2020)[48]"showed that in the test dataset 1, the model diagnosing osteoporosis achieved an AUC of 0.767 (95% confidence interval [CI]: 0.701–0.824) with sensitivity of 73.7% (95% CI: 62.3–83.1), the model diagnosing osteopenia achieved an AUC of 0.787 (95% CI: 0.723–0.842) with the sensitivity of 81.8% (95% CI: 67.3–91.8); In the test dataset 2, the model diagnosing osteoporosis yielded an AUC of 0.726 (95% CI: 0.646–0.796) with the sensitivity of 68.4% (95% CI: 54.8–80.1), the model diagnosing osteopenia yielded an AUC of 0.810 (95% CI, 0.737–0.870) with the sensitivity of 85.3% (95% CI, 68.9–95.0). Accordingly, a deep learning diagnostic network may have the potential in screening osteoporosis and osteopenia based on lumbar spine radiographs. However, further studies are necessary to verify and improve the diagnostic performance of DCNN models".

Zhou, J., et al. (2020)[49]"demonstrated the feasibility of automated segmentation of vertebral bodies using deep learning models on water-fat MR (Dixon) images to define vertebral regions of interest with high specificity. These regions of interest can then be used to quantify BMF with comparable results to manual segmentation, providing a framework for a completely automated investigation of vertebral changes in CLBP".

Zhou, Y., et al. (2019)[50]"proposed a novel detection algorithm based on deep learning. They apply a similarity function to train the convolutional network for lumbar spine detection. Instead of distinguishing vertebras using annotated lumbar images, their method compares similarities between vertebras using a beforehand lumbar image. In the convolutional neural network, a contrast object will not update during frames, which allows a fast speed and saves memory. Due to its distinctive shape, S1 is firstly detected and a rough region around it is extracted for searching for L1–L5. The results are evaluated with accuracy, precision, mean, and standard deviation (STD). Finally, our detection algorithm achieves an accuracy of 98.6% and a precision of 98.9%. Most failed results are involved wrong S1 locations or missed L5. The study demonstrates that a lumbar detection network supported by deep learning can be trained successfully without annotated MRI images. It can be believed that our detection method will assist clinicians to raise working efficiency".

III. PROPOSED METHODOLOGY

For the purpose of this study, 2D images will be used instead of 3D volumetric DICOMImages. The IVDs are not assigned with labels because the proposed area of study in this research willbe related to spinal curvature estimation andassociated VB measurements. Emphasis is made on the shape and size of the VB aswell as the distance between each of the VB, keeping in view the area of interestfor the spinal surgeons.The dataset will be tailored as per the research requirement and preference by selecting514 out of total 515 images in the dataset. A single scan is dropped as it was foundunsuitable for evaluating purposes in sagittal view, particularly L1 VB, however,presented ample information and details regarding IVDs in axial views. RadiAntDICOM Viewer by Medixant will be used to read the MR DICOM images whileImage Labeler Toolbox of MATLAB 2020a, to assign the pixel level labels. Themethod comprises of three steps involving image extraction, label assignment andlabel validation as given in the fowchart diagram as given in Figure 6.

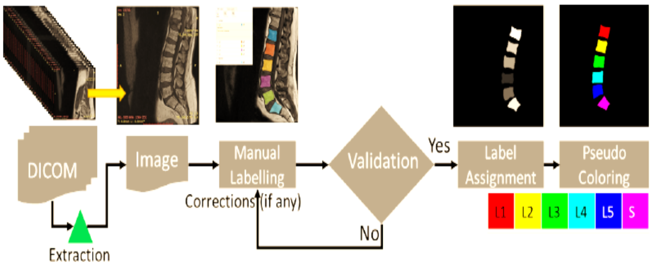

Figure 6. Process Flowchart

VI. CONCLUSION

From the present investigation, it is concluded that intended purpose of proposed autonomous lumbar spine toolkit is not to replace the role of clinicians but to introduce a vote of condence and reliability to their performed manual diagnosis. With the adoption of proposed the toolkit, clinicians may enable themselves with reliable quantitative metrics thereby adding precision to the selected/shortlisted surgical intervention procedure.

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