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TOPICAL REVIEW

A Critical Analysis on Vertebra Identification and Cobb Angle Estimation Using Deep Learning for Scoliosis Detection

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ABSTRACT Scoliosis is a complicated spinal deformity, and millions of people are suffering from this disease worldwide. Early detection and accurate scoliosis assessment are vital for effective clinical management and patient outcomes. The Cobb Angle (CA) measurement is the most precise method for calculating scoliotic curvature, which plays an essential role in diagnosing and treating scoliosis. This letter has conducted a systematic review to analyze scoliosis detection by vertebra identification and CA estimation using the Preferred Reporting Item for Systematic Review and Meta-Analysis (PRISMA) guidelines. The major scientific databases such as Scopus, Web of Science (WoS), and IEEE Xplorer are explored, where 2017-2023 publications are considered. The article selection process is based on keywords like "Vertebra Identification," "CA Estimation," "Scoliosis Detection," "Deep Learning (DL)," etc. After rigorous analysis, 413 articles are extracted, and 44 are identified for final consideration. Further, several investigations based on the previous work are discussed along with its Proposed Solutions (PS).

INDEX TERMS Vertebra identification, scoliosis detection, CA measurement, DL, convolutional neural network (CNN).

I. INTRODUCTION

Scoliosis is defined as the deformation of the spine structure caused by 'S' or 'C' shaped curves in the spine [1]. It is a structural deviation of the spine involving lateral and rotational curvatures, frequently emerging in young children around puberty or slightly before, leading to functional impairment. Individuals with scoliosis diagnosis might report various symptoms, such as a curved spine, a hunchback appearance, difficulty maintaining an upright posture, uneven shoulder levels, and visual concerns related to body asymmetry or deformity. Patients with this condition may suffer from physical and psychological issues such as early-stage back pain or discrimination due to biological differences [2], [3].

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At the time of diagnosis, orthopedists use manual examinations to diagnose the curvature of the spine, but sometimes it is challenging. The most common methods for clinical scoliosis examination are Spinal X-ray, CT scan, or MRI, as shown in Figure 1. For the treatment of identified scoliosis, it is essential to check the spinal curvature angle using CA measurement. The CA is frequently used to measure spinal curvature and aid in scoliosis diagnosis.

To evaluate the extent of spinal deformities, clinicians often rely on CA, which is determined using a back-to-front X-ray (posteroanterior). These angles are calculated by identifying the most rotated vertebrae in relation to a horizontal reference line in the upper and lower portions of the spine [4], [5], [6]. The three main CAs curves of the entire spine are the Proximal Thoracic (PT), Main Thoracic (MT), and Thoracolumbar/lumbar (TL). A structural PT curve is identified

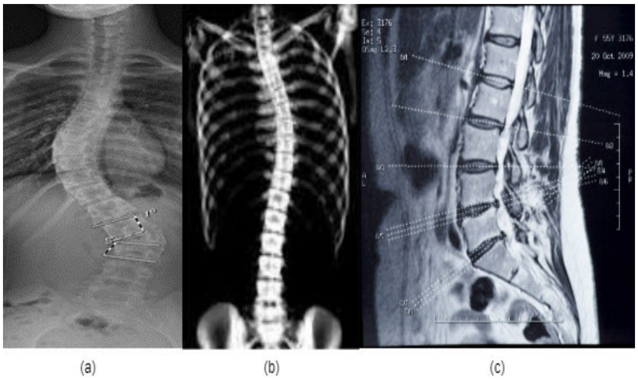

FIGURE 1. Samples of Scoliosis (a) X-ray, (b) CT-Scan, and (c) MRI.

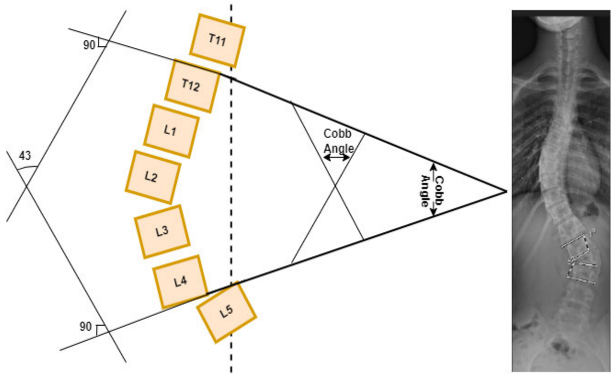

FIGURE 2. CA measurement.

when the residual coronal curve is equal to or exceeding 25^0 and T2 – T5 Kyphosis is greater than or equal to 20^0, irrespective of the coronal flexibility. Similarly, a structural MT curve is determined when the residual coronal curve equals or exceeds 250 and Kyphosis measures T10 – L2 measures 20^0 or more. Likewise, the TL curve is recognized when the residual coronal curve is greater than or equal to 25^0 and Kyphosis T10 – L2 measures 20^0 or more [7]. A high risk of scoliosis is indicated by the fact that one of them exceeds 10 degrees.

The CA cannot be measured manually because it is laborious, operator-dependent, and subject to large inter and intra-observer variability [8]. CA is known to vary from person to person, with a range of 10 to 20 degrees for mild scoliosis, 20 to 40 degrees for intermediate, and greater than 40 degrees for severe scoliosis [9]. It might be an arbitrary criterion that ends up influencing patient treatment in the wrong way. Therefore, it is imperative to use automatic estimates to increase the CA measurement's reproducibility [10]. Due to the irregular nature of deformities (e.g., different positions of curve and combinations) and the substantial variability in X-rays (due to various equipment with different technicians), these methods have a restricted level of precision and cannot be directly applied in clinical scenarios [11]. With recent developments in DL technologies, CA measurements can directly or indirectly identify CA from X-rays (as shown in Figure 2) that are limited to a single curve, but they are unable to handle heterogeneous patterns of curves. To calculate the CA, a line is drawn at the superior endplate, or top edge, of the most tilted upper vertebra and at the inferior endplate, or bottom edge, of the most tilted lower vertebra. After that, lines are drawn at the most inclined vertebrae that are perpendicular to each other. The angle measured at their intersection is known as the CA. This process will produce two parallel lines with an angle of '0' in a regular spine. The vertebrae in scoliosis are angled in accordance with the degree of curvature. The CA is the accepted measurement used to identify scoliosis and determine whether a curvature is stabilized or is becoming worse. After analyzing the previous studies, it is identified that the measurement of the CA is insufficient.

TABLE 1. Degree of CA measurement.

Category of the Scoliosis	Degree of CA
Normal	$< 10^0$
Mild	10^0 - 25^0
Moderate	25^0 - 40^0
Severe	$> 40^0$

Consequently, some Machine Learning (ML) methods that can recognize the CA automatically are required. The degree of the CA measurement for the detection of Scoliosis is shown in Table 1.

The latest advancements in medical Artificial Intelligence (AI) are primarily led by DL models, illustrating effective outcomes throughout the most intricate diagnostic and therapeutic research scenarios. Compared to conventional methods (ML), DL techniques exhibit more promising results in medical diseases like scoliosis, spondylosis, tumors, spinal stenosis, vertebral fractures, degenerative disc disease, etc. Such techniques could serve as valuable tools for aiding physiotherapists and patients in accurately diagnosing and determining the appropriate treatment path for scoliosis.

Getting an early prediction for scoliosis identification is essential and challenging due to having fewer resources. This study investigates different CNN models (i.e., U-Net, Deep Residual UNet, Fully CNN, etc.) for automatic early prediction of Scoliosis disease. Different datasets, CSI MICCAI, X-ray, CTSpine1K, etc., are available to train the above-mentioned models. These models may help the orthopedic practitioner to diagnose scoliosis disease. In addition, it may be helpful for the practitioner to recommend the patients based on the degree of CA measurement. Further, this study explored proposed solutions for the extracted investigations based on previous work done by the researchers in this field.

Further, this paper is organized into the following sections. PRISMA guidelines-based extraction of articles for the analysis of Scoliosis detection is discussed in section II. Investigations extracted from the researcher's previous work are discussed in section III. Section IV presents the review methodology of this critical review analysis. Section V

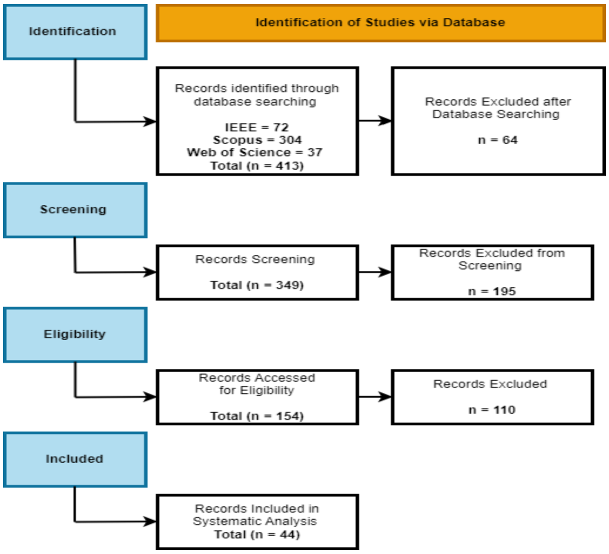

FIGURE 3. Systematic review of the vertebra identification and CA estimation for scoliosis detection.

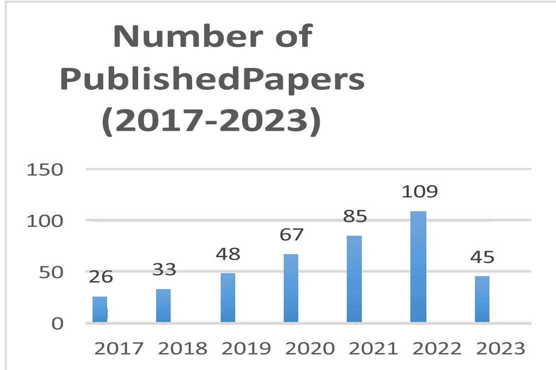

FIGURE 4. Number of published papers from 2017-2023.

FIGURE 5. Number of selected papers (2017-2023).

TABLE 2. Search criteria.

Sources	IEEE Xplore, Scopus, WoS
Keywords	Vertebra Identification, CA Estimation, Scoliosis Detection, DL, CNN
Query	"Vertebra Identification" OR "CA Estimation" OR "Scoliosis Detection" AND "Deep Learning"
Number of Articles	413

includes proposed solutions for investigations addressed in section III. Finally, this work is concluded in section VI with its future perspective.

II. REVIEW PROCESS: PRISMA GUIDELINES

The critical review analysis for identifying vertebra and estimation of CA to detect Scoliosis is discussed in this section. All the phases of this critical review analysis are shown in Figure 3. A total of 413 articles are collected from three popular databases (such as IEEE, Scopus, and WoS) using the keywords mentioned in Table 2. This process considered the articles published from 2017 to 2023, as shown in Figure 4. In the screening phase, all the collected manuscript (i.e., 413) records are checked manually, and 64 are excluded due to duplicate records. Further, the left records (413 - 64 = 349) are reviewed with their title and abstract, and 195 are excluded due to unrelated to the present study. Next, in the eligibility phase, from the left records (349-195 = 154), 110 articles are removed as they are out of scope. After completing the process, the left articles (154-110=44) are included in this study, as shown in Figure 5.

The article selection process for this proposed study is based on quality content parameters like year, findings, relevance, technology, research report, and availability. The

TABLE 3. Facts and figures.

S. No	Facts	Figures (Information)
1.	Year	All the finalized manuscripts are collected from 2017 onwards.
2.	Findings	Considered the research work that is focused on vertebra identification, CA estimation, and scoliosis detection.
3.	Relevant	Only those research papers detected vertebra identification, CA estimation, and scoliosis detection.
4.	Techniques & Technology	DL-based manuscripts are finalized for the proposed work.
5.	Research Report	Experimental result-based analysis reports are included.
6.	Availability	Consider only those articles that are related to the subject and are available on the web.

full-text articles are filtered using eligibility and inclusion criteria. As a result, 44 articles in total are included in the systematic review. Table 3 represents these parameters based on Eligibility and Inclusion standards.

III. BACKGROUND STUDY

This section performs a critical analysis of previous work done by different researchers to measure the CA for Scoliosis using DL techniques (as shown in Table 4), along with the various proposed investigations based on the literature.

A. ANALYSIS OF SCOLIOSIS DETECTION

Goral and Kose [1] developed a Decision Support System based on DL, capable of diagnosing scoliosis and generating treatment plans following the Schroth method. The system analyzed X-ray images to identify 68 specific vertebrae points and calculate CA using an interpretable and explainable Capsule Neural Network (CapsNet) model. The CapsNet model achieved most significant evaluation results, including Mean Squared Error (MSE) of 0.0038, Pearson Correlation Coefficient (PCC) of 0.93, and Accuracy of 0.98. Liang et al. [2] presented a comprehensive two-stage approach to address the challenges of avoiding reliance on unreliable landmarks while maintaining adaptability for clinical applications. The authors used two networks, LocNet and SegNet, in the first identification stage to precisely locate vertebrae and segment the complete spine, consequently reducing false positives. Subsequently, the authors also introduced the RegNet regression network to predict the bending directions of the localized vertebrae precisely. RegNet leverages RoIAlign-pooling to inherit cropped areas from LocNet's intermediate features, focusing solely on learning feature residuals. The proposed strategy demonstrated considerable improvements, with a minimum improvement of 16.81% and 6.15% on the well-known AASCE dataset. As a result, the error rates for CMAE were 2.92 2.34, and for SMAPE were 6.87 6.26%. Chen et al. [3] introduced FCNN for identifying and localizing vertebra from the CT images. The authors developed an FCN pipeline that enables the system to train classification FCN precisely at the vertebral level. They used MICCAI dataset for the experimental work and reduced the localization error from 9.10 ± 7.20 to 4.33 ± 6.31. Kim et al. [4] suggested a DL-based method for measuring CA, designed to be visually explainable and aligned with a clinician's decision-making process. Traditional DL techniques focused solely on estimating the CA without providing clinically informative spinal structure details. Conventional segmentation-based approaches offered spinal structure information but had limitations in accurately determining CA. The Digital Imaging Group in London, Canada, supplied the spinal AP X-ray images and the corresponding labels for training and evaluation. All X-ray images were sourced from individual patients, with 481 AP X-ray images allocated for training and 128 for testing. The training dataset was divided into 431 and 50 subsets for actual training and validation. The labeled data encompassed three CA and 68 landmarks representing the four corner points of 12 thoracic and 5 lumbar vertebrae. Qin et al. [5] introduced an end-to-end internal regression localization and multi-label classification network to identify vertebra. The authors employed a multi-label classification network to capture short- and long-context information about the vertebrae simultaneously, enhancing the identification accuracy. The evaluation was conducted on the MICCAI dataset, comprising 302 images divided into 242 training samples and 60 testing samples. This work achieved a 91.1% identification rate and a 2.2 mm localization error.

Zou et al. [6] introduced an innovative DL approach named Vertebra Localization and Tilt Estimation Network (VLTENet). The suggested methodology combines a High-Resolution Network with an FCN U-Net design to increase the accuracy of the CA estimate. The network's main goals was to predict vertebral localization and tilt estimation. The authors conducted experiments using both the AASCE and a custom dataset to determine the effectiveness of the discussed model. The outcomes showed that the suggested method for automating scoliosis assessment was effective. Chen et al. [8] discussed a novel technique called Adaptive Error Correction Net (AEC-Net) for accurately estimating CA from spinal X-ray images. The authors proposed two innovative approaches: a) AEC-Net incorporates two separate networks for calculating landmarks and CA independently, and b) introduced a unique loss function within AEC-Net to compute the final CA based on the two angles estimated above. The model was tested on a dataset comprised of 581 spinal X-ray images, achieving impressive results with 0.903, 0.906, and 0.945 for the PT (Pelvic Tilt), MT (Main Thoracic), and TL (Thoracolumbar) angles, respectively. Homg et al. [9] proposed a CNN method for the CA measurement of the spine from the X-ray images. They first reduced the image size and then chose the region of interest by projecting the horizontal and vertical histograms. For the segmentation of the vertebrae, the authors used U-Net, Dense U-Net, and Residual U-Net. They used 595 vertebrae images for the experimental analysis and achieved 95.1% Dice Coefficient Similarity (DSC). Liao et al. [10] proposed an approach for detecting and localizing vertebrae in spinal CT images for short- and long-range contextual information. The authors introduced a robust and effective method that can integrate contextual details from nearby and distant regions. A 3-D multi-tasking FCNN was designed to extract the short-range contextual information efficiently. For the experimental work, the authors used a publically available dataset consisted of 302 CT Scan images. Out of 302, 242 images were used for training and 60 for testing with a size of $96 \times 256 \times 256$. The model was trained over 12 epochs with a 256 batch size and a 10-6 learning rate. After the training of the model, 52.39% accuracy was achieved with a 7.03% error rate. Zhang et al. [11] predicted coronal spine alignment using smartphone-acquired radiograph images of scoliosis patients. The authors selected a total of 367 patients who regularly attended a scoliosis clinic and used smartphones to capture the coronal X-ray images. The objective was to develop an automated system for predicting CA regardless of image quality and without restrictions on curve patterns. The authors employed a neural network called SpineHRNet to identify crucial landmarks such as endplates and end-vertebrae. The model was trained on 294 randomly chosen images for each cross-validation iteration, with the remaining 73 images reserved for testing. The study found statistically

TABLE 4. Summary of the literature survey.

Paper	Title	Dataset	Purpose	Results
[2]	Accurate CA Estimation on Scoliosis X-Ray Images via Deeply-Coupled Two-Stage Network With Differentiable Cropping and Random Perturbation	AASCE	Instead of localizing the raw landmarks, which is inaccurate, or directly regressing CA from the entire X-ray image, which is rigid, the authors developed a novel two-stage end-to-end method for an accurate and flexible CA estimation via predicting the intermediate vertebral bending directions.	90.00 ± 2.78 Dice Coefficient
[13]	RUnT : A Network Combining Residual U-Net and Transformer for Vertebral Edge Feature Fusion Constrained Spine CT Image Segmentation	CTSpine 1K and VerSe 20	The RUnT network combines the residual U-Net feature extraction network with the Vision Transformer structure for quick and effective automatic segmentation of numerous vertebrae in the spine.	88.4% and 81.5% DSC
[18]	Automated Adolescence Scoliosis Detection Using Augmented U-Net With Non-square Kernels	AASCE – MICCAI 2019	The authors proposed a unique segmentation architecture for spinal CA estimation to achieve better segmentation results. This architecture uses pre-existing knowledge about the target shapes and applies certain non-square kernels.	9.2 % SMAP
[29]	Clinically experienced doctors used the LableImg tool to label the MRIs of 604 patients. Then, deep transfer learning models of YOLOv3, YOLOv5, and PP-YOLOv2 were created and trained on the Baidu PaddlePaddle framework to select an appropriate object detection algorithm.	Medical Images from Guilin People's Hospital	Clinically experienced physicians labelled 604 patients' MRIs using the LableImg technology. Deep transfer learning models of YOLOv3, YOLOv5, and PP-YOLOv2 were developed and trained using the Baidu PaddlePaddle framework to choose an effective object identification algorithm.	90.08% overall accuracy
[40]	Automatic vertebrae localization and segmentation in CT with a two-stage Dense-U-Net	CSI 2014	The authors proposed a two-stage Dense-U-Net DL method for automatic CT vertebrae segmentation and localization.	0.877 ± 0.035 Dice Coefficient

significant correlations ($p < 0.01$) between the predicted CAs and the Ground Truth (GT). Compared to the GT, the mean absolute error in the estimated CAs across various spinal regions ranged from 3.73 to 4.150, with a standard deviation ranging from 0.8 to 1.70.

Zhang et al. [12] presented the LPAQR-Net (Lightweight Pyramid Attention Quick Refinement Network), an effective and precise technique for segmenting vertebrae. Three essential components were included in LPAQR-Net: a) An attention-based Atrous Spatial Pyramid Pooling (A-ASPP) module was used to extract weighted pyramid contexts to enhance the vertebrae segmentation, b) To balance speed and accuracy, the authors developed the Lightweight Backbone Network (LB-Net) to reduce the requirements of the network and memory utilization, c) The model included a collection of Global Attention Refinement (GAR) modules for the refinement of the features. The proposed model was trained on the AASCE 2019 dataset that consisted of 431 X-ray images of the spine. The 50 images were used for validation and 128 for testing. The results showed an impressive performance, with a 93.09% Dice Coefficient (DC), 87.13% Jaccard Coefficient (JC), and 91.37% Sensitivity (SE). Xu et al. [13] proposed the Residual UNet (RUnT), a fusion of the Residual U-Net Feature Extraction Network and the Vision Transformer structure, aiming to swiftly and accurately segment multiple spinal vertebrae. Initially, the proposed model was utilized to extract profound vertebral features, preventing gradient diffusion and enhancing the precision of vertebral contour segmentation. Subsequently, an edge segmentation module received multi-scale feature maps generated by the residual structure, which offered abundant surface information about the vertebrae. Two datasets (i.e., CTSpine1K and VerSe 20) were used to evaluate the model. After training, the model achieved an 88.4% Dice Similarity Coefficient (DSC) on CTSpine1K and 81.5% on the VerSe 20 dataset. Naik et al. [14] developed a framework that accurately determines vertebral levels in intraoperative settings, achieving an average mean Point-to-Point Distance Error (mPDE) of 0.36 mm. The method for identifying vertebral levels and posture estimation and measuring PDE and computational speed fell well within the acceptable clinical range. This developed system could assess spinal deformations between preoperative and intraoperative images by individually registering each vertebra. Although the framework's main purpose is to discover and recognize vertebral centroids in intraoperative images, its adaptability enables it to expand its applications to estimate other anatomical postures in various preoperative and intraoperative imaging conditions. Tavana et al. [15] suggested using DL techniques to classify different types of spinal curvatures based on radiography images. Support Vector Machines (SVM), k-nearest Neighbours (kNN), and pre-trained neural network models such as Xception and MobileNet V2 were used in this work. The dataset consisted of 1000 AP (anterior-posterior)) X-ray images of the spine were obtained from Tehran, Iran's Shafa Hospital. Due to the relatively limited size of this private dataset, transfer learning was applied. According to the experiment's findings, pre-trained Deep Neural Networks distinguished between C-shaped and S-shaped spine curvatures about 10% more accurately than traditional methods for categorizing different types of spine curvature, pre-trained models like Xception and MobileNet V2 outperformed conventional machine learning methods because of their automatic feature extraction abilities. SVM served as the key activation function for gradient control. In terms of accuracy, the proposed model achieved rates of 92% for Artificial Neural Networks (ANN), 95% for SVM, 92% for KNN, and 96% for both MobileNet V2 + SVM and Xception + SVM in the experimental work.

Zhao et al. [16] proposed a fully automated U-Net method for CA measurement to address the precision issues associated with human measurements. They improved the U-shaped network by incorporating multi-scale feature fusion through the Inception Block, which replaced the U-shaped network's convolution kernel. Additionally, the authors integrated CBAM into the U-shaped network to enhance feature extraction accuracy. The authors suggested an efficient automated CA measurement method based on the segmented vertebrae. The authors conducted tests on 75 spinal X-ray images, achieving significant improvements in the Dice coefficient—32.03%, 33.58%, 12.42%, 5.65%, 4.55%, 4.42%, and 3.27% higher compared to DeepLabV3+, FCN8S, SegNet, U-Net, U-Net++, BASNet, and U2Net, respectively. Meng et al. [17] introduced a method that combines graph optimization and an anatomical consistency cycle for accurately localizing, segmenting, and identifying vertebrae. This approach specifically addresses the challenge of identifying transitional vertebrae by incorporating the configurations into a graphical model that integrates predictions from local deep networks, resulting in highly anatomically accurate outcomes. After refining the annotations, the authors achieved an initial Dice score of 92.8%, which improved to 96.5%. Wu et al. [18] discussed the use of a U-Net model with non-square kernels for automating the detection of adolescent scoliosis. The discussed approach involved two main steps: The authors first used the U-Net architecture to segment vertebrae. The second step in this work involved filtering out undesirable landmarks and extracting landmark coordinates from the segmented vertebrae using a non-learning-based method. The authors evaluated the method's performance using the ground truths from the AASCE-MICCAI challenge 2019 dataset. The findings showed a 9.2% symmetric mean absolute percentage error, with variances of less than 10 degrees occurring in 90% of the estimates. Tang et al. [19] suggested a method for detecting scoliosis based on feature extraction from a specific region of interest. The proposed approach involved several steps: initially, the authors gathered patient back images and enhanced them through pre-processing. Subsequently, the authors segmented the images based on the relevant back region, then extracted the contour of the back, marked feature points, and assessed the degree of scoliosis by examining the symmetry of posture characteristics and calculating the CA of the spine's midline. The analysis of the experimental data demonstrated that this scoliosis detection method provided an initial evaluation of postural aspects. Specifically, when the patients had CA ranging from 0 to 30 degrees, the error in scoliosis identification fell within an acceptable range, typically between 0 and 4 degrees.

Ishikawa et al. [20] presented a DL algorithm to predict the CA. This study had two main objectives: (1) to assess the performance of this DL algorithm in forecasting the CA and (2) to evaluate the algorithm's predictive accuracy. The study involved 100 patients potentially affected by Adolescent Idiopathic Scoliosis (AIS). The mean absolute error was 4.7, the root mean square error was 6.0, and the correlation coefficient between the expected and observed CA was 0.87. Sun et al. [21] explored the use of DL-based key point detection technology to assess the CA in cases of Idiopathic Scoliosis. 181 anterior-posterior spinal X-rays were used in this investigation, including 16 cases of adults without scoliosis and 165 cases of idiopathic scoliosis. After labelling each image, the authors randomly selected 145 for training and 36 for testing. For the test cases, manual measurements yielded a mean CA of 27.4° ± 19.2° (ranging from 0.00 to 91.00°), while automated measurements resulted in a mean CA of 26.4° ± 18.9° (ranging from 0.00 to 88.00°). The automated approach took an average of 4.45 seconds to measure each radiograph. Abedi et al. [22] proposed an adaptive neuro-fuzzy interface technique to calculate the primary thoracic Cobb and thoracic kyphosis angles in teenage patients with idiopathic scoliosis after surgery. The system's reliability was used to evaluate the root mean square errors, clinical corrective deviation indices, and the ratio of projected post-operative angles to actual post-operative angles seen after surgery. The results indicated errors of 3.0° for post-operative CA and 6.3° for thoracic kyphosis angles. Fraiwan et al. [23] discussed the use of DL technology for detecting scoliosis and spondylolisthesis from X-ray images. The authors gathered a dataset of 338 actual X-ray images, comprising 188 cases of scoliosis, 79 cases of spondylolisthesis, and 71 from healthy individuals. DL models were employed to perform binary classifications among these three classes. The results on this dataset showed an impressive performance, with the highest mean accuracy reaching 96.73% and a maximum accuracy of 98.02%. Tavana et al. [24] suggested an effective ensemble technique for identifying the type of spinal curve through the utilization of Deep Transfer Learning (DTL) and a Soft Voting Classifier (SVC). The scoliosis resulted in a C- or S-shaped deformity. For the experimental work, they used a dataset consisting of 1000 AP spine X-rays from the Shafa Hospital in Tehran, Iran. Deep transfer learning was adopted due to the relatively small dataset size, and the study assessed the accuracy of pre-trained networks such as MobileNetV2, Xception, ResNet152, InceptionV3, and pre-trained DenseNet121. Masood et al. [25] introduced a method involving DL techniques for vertebral body segmentation, classifying spine disorders, and extracting spinal measurements. The accuracy of the classification of spondylolisthesis was 89% when they used the angular deviation metric, and it was 93% when they evaluated the region of the lumbar curve to identify the patients' level of lumbar lordosis (LL). The proposed approach utilized ResNet-UNet for the semantic segmentation of vertebral bodies (VBs), achieving impressive performance metrics with a Dice Similarity Coefficient (DSC) of 0.97 and Intersection over Union (IoU) of 0.86. Yao et al. [26] introduced a fully automated system for measuring cervical spinal curvature using the CA method on X-ray images. This system aims to alleviate the workload of medical professionals and provide a foundation for surgical decisions. The method employed a Hybrid Transformer Network (HTN) that combined feature fusion, self-supervised learning, and a self-attention mechanism. The authors used a new dataset for cervical spondylosis along with the AASCE MICCAI 2019 challenge dataset to assess the model's performance. The results of the experiments showed a Symmetric Mean Absolute Percentage Error (SMAPE) of 11.06% and a significant Pearson correlation coefficient of 0.9619 ($p < 0.001$).

Fatima et al. [27] proposed an automated approach for vertebrae localization and segmentation to estimate CA and assess curvature deformities. They applied YOLO techniques on the Mendeley and CSI 2016 datasets for the experimental work. In the result analysis, they achieved 98.04% Mean Average Precision (mAP) for the Mendeley and 81.25% for the CSI 2016 dataset. Additionally, this method effectively classified Lumbar Lordosis using the corner point Cobb estimation method, demonstrating high accuracy rates. Sha et al. [28] presented a novel model based on YOLOv3-tiny for identifying three different spinal fractures, i.e., cervical, thoracic, and lumbar fractures. To optimize the model's efficiency, the authors replaced YOLOv3-tiny's conventional convolutional layers with fire modules sourced from SqueezeNet, reducing the model's parameters and overall size. As a result of the experimentation, the downsized model was a mere 13 MB, approximately one-third of the size of YOLOv3-tiny, while maintaining robust lesion detection performance. The model achieved an impressive mAP of 90.7% and an Intersection Over Union (IOU) of 91.3%. Xuan et al. [29] introduced a set of DL techniques for diagnosing spinal diseases using MRI images. In this work, the authors used YOLOv3, YOLOv5, and PP-YOLOv2 for the training. Based on the experiments, the PP-YOLOv2 model exhibited an impressive overall diagnostic accuracy of 90.08% for normal cases, IVD bulges, and spondylolisthesis. This accuracy surpassed YOLOv3 and YOLOv5 by 27.5% and 3.9%, respectively. In practical applications, this software provided a supplementary diagnosis for an MRI image of a patient with spinal disease in less than 14.5 seconds. It achieved an accuracy rate of 90.08%, comparable to that of expert doctors. This development significantly enhances diagnostic efficiency, reduces the risk of missed or incorrect diagnoses, and offers substantial societal benefits. Mushtaq et al. [30] explored the localization and segmentation of the lumbar spine, which is instrumental in studying lumbar spine abnormalities. The authors employed YOLOv5, the latest iteration in the YOLO family, as it offered a lightweight and swift object detection solution. YOLOv5 achieved an impressive Mean Average Precision (mAP) score of 0.975 for accurately localizing the lumbar spine. The authors established a connection between the angles and the region size, determined from YOLOv5's centroid calculations, to identify lumbar lordosis, achieving an accuracy rate of 74.5%. For segmenting the vertebrae and the edges, the authors processed cropped images extracted from YOLOv5 bounding boxes through HED U-Net, a system that combines edge detection and segmentation techniques. Subsequently, the authors utilized a Harris corner detector to pinpoint the corners of the vertebrae, enabling them to derive Lumbar Lordotic Angles (LLAs) and lumbosacral angles (LSAs). Zheng et al. [31] introduced the Automatic Detection and Measurement of the Spinous Process (SP) Curve on Clinical Ultrasound Spinal Images. They also introduced the Gradient Vector Flow Snake model (GVF) for the automatic Spine Position localization in transverse ultrasound images. For the experimental work, 50 individuals with varying degrees of scoliosis were tested, and two observers manually computed SPA values from both ultrasound images and radiography. The outcomes showed that the ultrasound and radiography techniques had a strong linear association ($r > 0.85$). The mean absolute differences (MADs) for the SPAs derived from the two modalities were 3.4 ± 2.4 and 3.6 ± 2.8, respectively. Banerjee et al. [32] proposed a Multi-scale SIU-Net (Skip-Inception U-Net) model for the identification and localization of vertebrae. To determine the severity of scoliosis, this architecture was created to automate and reliably identify bone characteristics. The proposed architecture comprises two primary components: a modified Inception block and newly devised dense skip connections on the decoder side. In this work, the authors used a dataset consisted of 109 spine ultrasound images. The authors evaluated their model based on the three metrics, i.e., Jaccard Index, Dice Coefficient, and Euclidean distance. It was compared with three other models: the fundamental U-net segmentation model, the UNet++ model, and the MultiResUNet model. The results demonstrated that the SIU-Net model produced the most precise segmentation results, particularly in critical areas of interest such as thoracic and lumbar bone characteristics. Furthermore, this approach exhibited the lowest histogram Euclidean distance (0.011) and the highest average Jaccard score (0.781) and Dice score (0.883) when compared to the other three models. Altini et al. [33] discussed the uses of CNN, K-Means Clustering, and K-NN for segmenting and recognizing vertebrae in CT scans. The proposed method involved a two-phase approach: first, a fully automated binary segmentation of the entire spine using a 3D CNN, and second, a semi-automated process that utilized conventional machine learning techniques to pinpoint the centroids of the vertebrae. The authors utilized a dataset comprising 214 CT scans from the VerSe'20 challenge for training, validation, and testing purposes, and also gathered 12 additional CT scans from patients with varying degrees of scoliosis from a nearby medical facility to evaluate the robustness of the segmentation and labeling algorithms. Notably, the vertebrae identification phase achieved a Dice coefficient of 90.09%, while the binary spine segmentation stage attained a binary Dice coefficient of 89.17%. Le Van et al. [34] introduced an autonomous system that used modified Vietnamese X-ray images to recognize lumbar implants and identified scoliosis. Due to the absence of appropriate X-ray medical imaging resources, two alternative approaches were employed. These approaches included utilizing transfer learning with the pre-trained models and pre-trained APIs. When compared to the pre-trained API models, the outcomes revealed that transfer learning was well-suited for the adapted Vietnamese X-ray imaging data. Additionally, transfer learning produced accurate results in a limited dataset of medical imaging while requiring less time for model training. Further, DenseNet has a high validation accuracy of 93.5% in comparison to ResNet's 8.25%, SqueezeNet's 81.5%, and InspectionV3's 87.5%. Fu et al. [35] presented a multi-task network for the automatic estimation of the CA Measurement. The authors proposed an automated architecture capable of estimating 68 landmarks distributed across 17 vertebrae through a combination of segmentation and landmark data. Additionally, the authors also take the spinal curvature defined by 68 landmarks into consideration, to calculate the CA. The effectiveness of this approach in enhancing landmark estimation accuracy and reducing CA measurement errors was demonstrated through extensive experiments involving 240 X-ray images. Kokabu et al. [36] suggested a Deep CNN along with three-dimensional depth sensor imaging for the detection of scoliosis. The authors employed Pearson's correlation coefficient analysis to establish the relationships between the real and predicted CA. Mean absolute error and root mean square error were used to evaluate the accuracy of the network models' predictions. The dataset, consisting of 160 data files, was randomly divided into five datasets (referred to as datasets 1, 2, 3, 4, and 5), and a five-fold cross-validation was carried out on each dataset. The correlation between the actual CA and the mean predicted CA was found to be 0.91. The root mean square error was 5.4, and the mean absolute error was 4.0. The mean projected CA achieved an accuracy of 94% in recognizing CA greater than 100 and 89% for angles exceeding 200 degrees.

Krizhevsky et al. [37] proposed an AI-powered platform for Auto Analyses of Spine Alignment. The researchers employed a large and deep CNN to classify a substantial dataset of 1.2 million high-resolution images from the ImageNet LSVRC-2010 competition into 1,000 different categories. This proposed model achieved impressive results on the test data, with top-1 and top-5 error rates of 37.5% and 17.0%, respectively. The researchers employed non-saturating neurons and a highly efficient GPU implementation for convolution operations to expedite the training process. Zhang et al. [38] introduced a Multi-Task Relational Learning Network (MRLN) that establishes connections between vertebrae and prioritizes three key tasks. The authors utilized a dilation convolution group to expand the receptive field and incorporated long short-term memory (LSTM) to retain historical knowledge about the sequential relationships among vertebral bodies. In the decoder phase, focusing on segmentation and localization tasks, authors introduced a co-attention module to grasp correlation information, namely localization-guided segmentation attention (LGSA) and segmentation-guided localization attention (SGLA). Additionally, the authors employed a strategy to prevent overfitting by jointly learning two tasks, allowing them to correct and complement each other. For the experimental analysis, the research team collected data from 407 patients across multiple centers and from various manufacturers. The data included diverse parameters such as a range of repetition times (TR) from 340 ms to 4,000 ms (with an average of 1965 ms), echo times (TE) ranging from 8.072 ms to 147 ms (with an average of 66.834 ms), flip angles (FA) between 90 and 180, slice thickness ranging from 0.88 mm to 4 mm (with an average of 2.4483 mm), and in-plane pixel spacing that varied. Tirindelli et al. [39] suggested a robotic ultrasound technique for the automated detection of vertebral levels. The proposed model combined force and ultrasonic data to deliver tactile and visual feedback that enhanced performance while working with potentially damaged data. The robotic arm automatically scanned the volunteer's back along the spine, using force-ultrasound data to identify vertebral levels. Vertebral level occurrences were indicated as peaks in the force trace when the robot applied controlled force to the patient's back. To derive a 1D signal representing the likelihood of a vertebra being present at each position along the spine, ultrasound data was processed using a DL approach. Cheng et al. [40] proposed a two-stage DL approach, Dense-U-Net, for automatically segmenting CT vertebrae. In the first stage, the authors used a 2D-Dense-U-Net to identify vertebrae by detecting the centroids in 2D slices with dense labeling. In the second stage, authors employed a 3D-Dense-U-Net to segment the specific vertebra within a region of interest determined based on the centroid location. The authors resampled the resolution after merging all segmented vertebrae to form a complete spine. The dataset was collected from CSI 2014 and evaluated the model using six metrics. For vertebrae segmentation, the model achieved a dice coefficient of 0.953 ± 0.014, an intersection over union of 0.911 ± 0.025, a Hausdorf distance of 4.013 ± 2.128 mm, and pixel accuracy of 0.998 ± 0.001. Vertebrae localization was evaluated with a location error of 1.69 ± 0.78 mm and a detection rate of 100% using these metrics. The authors also demonstrated the method's generalizability by evaluating it on the xVertSeg challenge dataset, achieving a location error of 4.12 ± 2.31, a detection rate of 100%, and a dice coefficient of 0.877 ± 0.035. Alrehily et al. [41] discussed the experiments to see how well Computed Tomography (CT) scans with scan projection radiography (SPR) for AIS evaluation work. When compared to conventional radiography, the proposed scanning modality emits less radiation. According to the study, a spinal deformity affected young children with Adolescent Idiopathic Scoliosis (AIS). To monitor the deformity, it is necessary to expose oneself to X-rays frequently, but this can subsequently result in radiation-induced cancer. The mean-variance between the established angle and the CA measured was 2.75 (with a standard deviation of 1.46). Compared to studies involving different imaging methods for determining the CA, there was substantial consensus among the observers (p-value = 0.861, 95% confidence interval: 0.70 to 0.95). Rehman et al. [42] described a method for predicting the shapes of vertebral bones using a DL framework in combination with a conventional region-based level set. The authors named this framework BFU-Net, which proved to be a robust and valuable tool for effectively segmenting fractured vertebrae. The proposed method underwent successful testing on two challenging datasets: one comprising 25 CT image data (comprising both healthy and fractured cases) from the spine segmentation challenge CSI 2016 or xVertSeg.v1 challenge, and another with 20 CT scans (15 healthy and 5 fractured cases) from the spine segmentation challenge CSI 2014. In the CSI 2014 dataset (encompassing lumbar and thoracic regions), the dice score was 96.4 ± 0.8% for non-fractured cases and 92.8 ± 1.9% for fractured cases. Similarly, in the CSI 2016 datasets (including 10 annotated CT datasets), the dice score for the overall 25 CT dataset was 95.4 ± 2.1%, and for the 15 CT datasets with provided ground truths, it was 95.2 ± 1.9%.

Zhang et al. [43] introduced the CGARD-VCM method, which combined the centroid method with a cascade gentle AdaBoost classifier and region-based DRLSE (Distance Regularized Level Set Evolution) to quantify spine curvature. This approach considered vertebral images with diverse perspectives, contrasts, and pathological abnormalities when training the cascade gentle AdaBoost classifier to incorporate more vertebral features. Furthermore, the identified vertebrae were assigned numerical labels to distinguish and separate the individual components of the spine. Alsiddiky et al. [44] proposed an Analytical Transform Assisted Statistical Characteristics Decomposition Model (ATS-CDM) for accurate segmentation of spinal tumors. This paper demonstrates the capability of automatic segmentation of lumbar spine structures when high-resolution MRI data and large-scale clinical datasets are accessible. The suggested analytical transform-assisted approach has desirable qualities, including strong noise resistance and suitability for analyzing with inherent pictures. The most likely form parameters for each subregion can be robustly selected using an optional model-fitting approach. Based on the segmentation outcomes, ATS-CDM demonstrated exceptional precision in segmentation across various individuals and spinal regions, achieved a remarkable accuracy of 98.7% for bending and 98.88% for segmentation. This translates into an average ROC grading of 94.2% ± 0.2% to 97.02% ± 0.2%, showcasing its high performance. Chuang et al. [45] introduced an Efficient Triple Output Network designed for vertebral segmentation and identification. The innovative architecture, featuring three distinct outputs, effectively utilizes memory resources while delivering excellent segmentation outcomes. In the experimental evaluation, the authors utilized the XvertSeg dataset, comprising 15 individual spine data points along with lumbar segmentation masks. This model demonstrated impressive performance, achieving a Dice coefficient of 92.6% in the segmentation task. Wang et al. [46] suggested Accurate Automated CA Estimation using Multi-View Extrapolation Net (MVE-Net). The MVE-Net consists of three distinct components: In the first section, the Joint-view net simultaneously learns the Anteroposterior (AP) and Lateral (LAT) angles by leveraging shared landmarks derived from a joint representation. The second section, the Independent-view net, focuses on learning the AP and LAT angles separately using landmarks specific to each angle's features. An Inter-error correction net is employed to learn a combination function and correct any errors from the first two networks to enhance angle estimation accuracy. The model's performance was assessed using 526 X-ray images, resulting in Circular Mean Absolute Error rates of 7.81% for the AP angle and 6.26% for the LAT angle estimation.

B. PROPOSED INVESTIGATION

After rigorous analysis for Vertebrae Identification and Scoliosis Detection using DL, some investigations are observed mentioned below:

- **Investigation 1:** What types of datasets are used for Vertebra Identification and Scoliosis Detection?
- **Investigation 2:** What are the best-suited DL models used by the researcher for Vertebra Identification and Scoliosis Detection?
- **Investigation 3:** What are the challenges faced during CA Measurement?
- **Investigation 4:** What open-source software is available for Scoliosis Detection?
- **Investigation 5:** What are the several causes behind

Scoliosis disease?

- **Investigation 6:** What are the different age groups of people affected?
- **Investigation 7:** What are the limitations of CA measurement?
- **Investigation 8:** How can we address these limitations in future research?

IV. RESEARCH METHODOLOGY

The methodology used to detect scoliosis and calculate the CA from the various X-ray images by the various researchers is shown in Figure 6. Multiple processes are involved in training a U-Net model to detect scoliosis, from data collection and pre-processing to model training and evaluation. The first stage is to gather the dataset that consists of both normal and scoliosis-related X-ray images. Ground truth labels are also included in the dataset to denote the existence and degree of scoliosis. Further, this dataset is fed into the U-Net architecture. Depending on the dataset and available computing

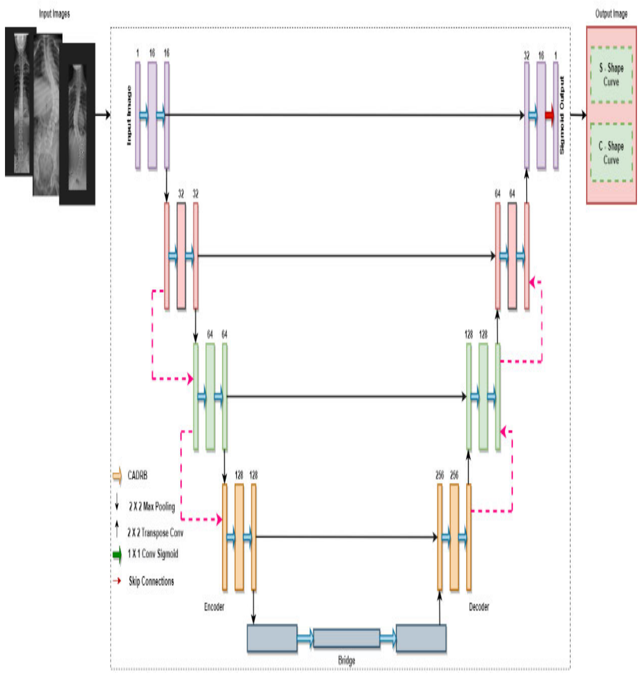

FIGURE 6. Deep residual U-net architecture for scoliosis detection.

ability, the number of layers, filters, and other hyperparameters can be modified. To avoid overfitting, use the appropriate dropout layers, normalization layers, and activation functions (like ReLU). Train the U-Net model on the training dataset using an optimizer like Adam or SGD. Evaluate the trained model on the test dataset to assess its performance.

The following evaluation measures are frequently used: accuracy, precision, recall, F1-score, and intersection over union (IoU). The proposed architecture consists of three stages:

A. ENCODING STAGE

During the encoding phase, a sequence of convolutional and pooling layers slowly decreases the size of the input image. Features from the input image are captured and extracted by each convolutional layer. The network can collect patterns of features since pooling layers minimize the spatial dimensions of the feature maps.

B. DECODING STAGE

The traditional U-Net network combines low-level details with high-level semantics via skip connections to enable feature enhancement. On the other hand, these feature maps may have redundant information in addition to characteristics that are difficult to detect. Consequently, network performance may be negatively impacted by directly combining the encoder and decoder characteristics through skip links.

C. MAPPING LAYER

The mapping layer connects the matching feature maps from the encoding and decoding phases. It helps with accurately localizing objects in the segmentation task by facilitating the merging of low-level and high-level characteristics. At the same spatial resolution, skip connections link feature maps straight from the encoding step to the decoding stage. With the use of these links, the network may segment data using both local and global context.

TABLE 5. Datasets used in scoliosis detection.

Dataset	Year	No. of Images	Datasets used to train the model	Link
CSI MICCAI	2014	374	[41], [35], [26], [39], [3]	http://csi workshop.weebly.com/challenges.html
Mendeley	2019	575	[26], [13], [34], [31]	https://data.mendeley.com/datasets/k57fr854j2/2
X-Ray Dataset	2022	581	[8], [30], [4], [20], [33], [11], [40], [22], [5]	https://www.kaggle.com/datasets/yasserhessein/the-vertebrae-xray-images
AASCE-MICCAI challenge 2019 dataset	2019	609	[2], [17], [1], [30], [29], [9]	https://aasce19.github.io/#challenge-dataset
xVertSeg dataset	2019		[44], [18], [28], [16]	https://osf.io/nqjyw/
3D Spine dataset	2022		[38], [10], [13], [15], [31] [21], [23]	https://www.kaggle.com/datasets/jirkaborovec/cervical-
				spine-fracture-detection-npz-3d-volumes
CTSpine1K	2022	1005	[37], [19], [12], [43], [45], [31]	https://github.com/MIRACLE-Center/CTSpine1K
VerSe 20 public datasets	2020	319	[42], [12], [32], [16], [43]	https://osf.io/t98fz/

V. DISCUSSION

This section explains the Possible Solutions (PS) for investigations discussed in section III.

Investigation 1: What types of datasets are used for Vertebra Identification and Scoliosis Detection?

P.S: Specific aspects of scoliosis detection datasets can differ between research studies because they are determined by the study's aims, accessible data, and methodologies. Table 5 shows the different datasets used by various researchers in their work. Here are some common criteria and traits found in past scoliosis detection research datasets:

a) The main components of many scoliosis detection datasets are lateral and posterior-anterior (PA) X-ray pictures of the spine.

b) Annotations of ground truth for CA are crucial parameters for training scoliosis detection models and representing the degree of spine curvature.

c) Data augmentation techniques, including rotation, flipping, and scaling, are frequently used to improve model generalization and boost dataset diversity.

TABLE 6. Different DL techniques used in scoliosis detection.

S. No	References	Paper Type	Focus	Used Algorithms	Problem(s) Addressed	Accuracy
1.	[2]	IEEE Journal Of Biomedical And Health Informatics	CA Estimation	RegNet and SegNet	Estimating the CA from X-ray Images of Scoliosis.	90.00 ± 2.78 Dice Coefficient
2.	[6]	IEEE Journal Of Biomedical And Health Informatics	Localization and Tilt Estimation Network for Automatic CA Estimation	VLTENet	This study proposed using the JS-Loss function to enhance spatial constraints by considering the structural characteristics of the spine. This approach enables the neural network to concentrate on the immediate vicinity of the spine while disregarding distant background regions.	5.44 % SMAPE
3.	[38]	IEEE Robotics And Automation Letters	Robotic Ultrasound Approach for Automatic Vertebral Detection	TCN Network	The TCN performed better using both force and image approaches, demonstrating its capacity to learn the input signal peaks and an anatomical prior on the locations of vertebral levels.	0.9538 Dice Coefficient And 0.997 AUC
4.	[3]	IEEE Transactions On Medical Imaging	Vertebrae Identification and Localization	FCN	A fully CNN operating in a 3D context, trained specifically at the spine level, was employed to gather extensive contextual information across CT volumes.	23.59% SMAPE
5.	[5]	IEEE Transactions On Neural Networks And Learning Systems	Vertebrae Labeling	Multi-Label Classification Network	An end-to-end integral regression localization and multi-label classification network was proposed to identify and localize vertebrae in CT.	91.1% Identification Rate
6.	[30]	IEEE Transactions On Ultrasonics, Ferroelectrics, And Frequency Control	Automatic Detection and Measurement of Spine Curve	Gradient Vector Flow (GVF) snake model	The highlighted vertebral structures were first extracted to calculate the initial curve, and the GVF snake model was then applied to automatically determine the SP tip position on transverse frames.	97.05% Accuracy
7.	[4]	IEEE Access	Automation of Spine Curve Assessment in Frontal Radiographs	M-Net Architecture	They used a fully convolutional structure and used the confidence map regression approach to locate and identify every vertebra. In contrast, standard coordinate regression methods only accept inputs of a limited size and call for deep layers with several network parameters.	7.84 SMAPE
8.	[1]	IEEE Access	CapsNet and Fuzzy Logic Decision Support System for Diagnosing the Scoliosis	CapsNet	This study aims to develop a decision support system based on DL for diagnosing scoliosis and generating treatment plans following the Schroth method.	98.00% Accuracy
9.	[44]	IEEE Access	Vertebral Segmentation and Identification	3D U-Net architecture	They proposed an iterative method for segmenting individual vertebrae instances, demonstrating robust applicability across all vertebra types, encompassing cervical, thoracic, and lumbar vertebrae.	98.88% Accuracy
10.	[11]	IEEE Access	Spine Alignment Prediction	SpineHRNet	This technique can have important clinical applications in AIS screening and follow-up by offering precise and portable CA detections for telemedicine, lowering experts' load for radiographic measures with better assessment consistency, and aiding deformity research.	83.0 % F1- Score
11.	[12]	IEEE Access	Vertebral Edge Feature Fusion Constrained Spine CT Image Segmentation	Runt	The deep vertebral features were first retrieved using the residual U-Net network to prevent gradient diffusion and increase the precision of vertebral contour segmentation.	88.73 ± 2.30 Dice Coefficient
12.	[17]	Canadian Association Of Radiologists' Journal	Scoliosis Detection	U-Net	The proposed Augmented U-Net segmentation architecture, which was robust in predicting CA from AP X-Ray images.	92.06 DSC
13.	[26]	Intelligent Automation & Soft Computing	Localization and Segmentation of Vertebrae for Cobb Estimation and Curvature Deformity	YOLO	This study describes an automated approach that was employed for the Cobb estimation-based deformities in spine curvature analysis.	11.06% SMAPE

d) To preserve class balance and avoid model bias, both positive sample cases with scoliosis and negative sample cases without scoliosis are included.

Investigation 2: What are the best-suited DL models used by the researcher for Vertebra Identification and Scoliosis Detection?

P.S: After the critical analysis, different DL algorithms are discussed in Table 6 for Vertebra Identification and Scoliosis Detection.

In the field of medical image analysis, DL models have demonstrated great potential, especially in tasks related to vertebral segmentation and CA measurement. While measuring the CA is critical for determining the severity of diseases such as scoliosis, segmentation of vertebrae is an important first step in identifying and analyzing spinal abnormalities. The above-mentioned DL models are the best models for the identification of scoliosis and CA measurement.

Investigation 3: What are the challenges faced during CA Measurement?

P. S: To determine the CA, one draws lines that run parallel to the upper edge of the upper vertebral body and the lower edge of the lowest vertebra within the curved section of the spine. Perpendicular lines are then extended from these parallels, and the angle formed where these vertical lines intersect referred to as the 'angle of curvature'. Some of the challenges that are faced during CA Measurement are mentioned below:

a) The CA can be measured differently by different observers, which could produce inconsistent findings. A person's unique interpretation of the vertebral endplates as well as their experience and training may have an impact on this.

b) Changes in measurement procedures, weariness, or developing interpretation standards can all lead to variations in measurements even from the same observer at various periods.

c) CA measurements can be inaccurate because to variations in radiography techniques, including patient placement and image quality. Errors may arise from uneven positioning or poor image quality.

d) Three-dimensional spinal abnormalities may be more complex than the CA can measure because it is a two-dimensional measure. CA may not accurately represent all the components of scoliosis in some circumstances.

Investigation 4: What open-source software is available for Scoliosis Detection?

P.S: Scoliosis can be identified using several free and open-source software programs, such as CobbMeter, Surgimap, CAMS (Compute Aided Measurement System), and the CA app. However, a lot of these systems mostly depend on manual labour and human input for critical tasks related to scoliosis recognition, like measuring angles or recognizing landmarks. Scoliosis can be identified using a number of free and open-source software programmes, such as CobbMeter, Surgimap, CAMS (Compute Aided Measurement System), and the CA app. However, a lot of these systems mostly depend on manual labour and human input for critical tasks related to scoliosis recognition, like measuring angles or recognising landmarks. Because observers differ, this manual approach can be laborious and add variability. Large datasets or the requirement for quick processing of a large number of medical images might present difficulties for open-source software, particularly in busy clinical environments with a high patient volume. On the other hand, as DL models are developed, they may provide an automated and effective solution by integrating easily with current healthcare operations. Additionally, DL models have the capability to offer enhanced insights into the decision-making processes involved in scoliosis recognition.

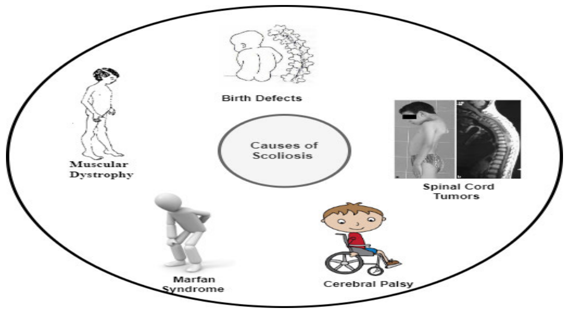

FIGURE 7. Several causes behind scoliosis detection.

Investigation 5: What are the several causes behind Scoliosis disease?

P.S: Various forms of scoliosis have distinct underlying causes, as illustrated in Figure 7. Medical professionals differentiate these curves into two categories: structural and non-structural. In non-structural scoliosis, the spine exhibits a curved appearance but functions normally. Several factors can lead to non-structural scoliosis, such as leg length discrepancies, muscle spasms, and inflammatory conditions like appendicitis. In contrast, structural scoliosis is characterized by a fixed and unalterable spine curvature. Some of the causes of Scoliosis are mentioned below:

- Muscular Dystrophy
- Birth Defects
- Tumors
- Cerebral Palsy
- Genetic conditions like Marfan syndrome and Down syndrome.

Investigation 6: What are the different age groups of people affected?

P. S: Roughly six to nine million individuals in the United States, constituting about 2 to 3 percent of the population, were estimated to experience scoliosis. While scoliosis can manifest in early childhood, it predominantly emerges between the ages of 10 and 15, affecting both genders equally. Notably, females have an eightfold higher likelihood of developing a curvature severe enough to necessitate treatment. Each year, over 600,000 people with scoliosis seek medical attention from private physicians, with approximately 30,000 children receiving braces and 38,000 individuals undergoing

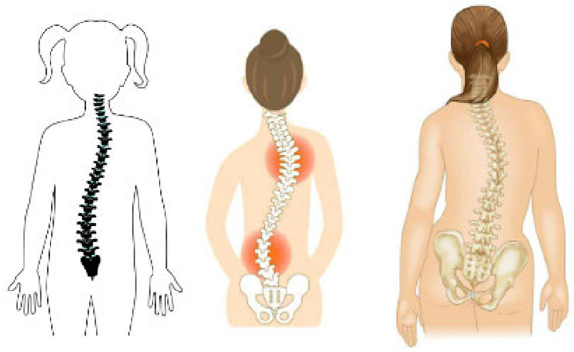

FIGURE 8. Age groups affected by scoliosis.

spinal fusion surgery. Some of the age groups that are affected by Scoliosis (shown in Figure 8) are mentioned below:

- **In Children**

Scoliosis in children is categorized based on age as follows:

a. Infantile (0 to 3 years old).
b. Juvenile (3 to 10 years old).
c. Adolescent (11 years old and older, or from the onset of puberty until skeletal maturity).

- **In Adults**

In the case of adults, the development or diagnosis of scoliosis differs from that in children due to varying underlying causes and treatment goals for individuals who have already reached skeletal maturity. Adults with scoliosis can be categorized into two groups:

a. Adult idiopathic scoliosis
b. Adult degenerative (or de novo) scoliosis

Although it is rare, adult scoliosis can also arise from illness, surgery, or trauma.

- **In Elderly**

According to one study, 68% of healthy individuals over the age of 65 who did not have low back discomfort had scoliosis. The following are common causes of scoliosis in older people:

a. Traumatic scoliosis (after injury or surgery)
b. A pre-existing adolescent scoliosis that has progressed
c. Degenerative (or de novo) scoliosis

Surgery is the only procedure that is advised to treat adult scoliosis. Surgery, however, can be far more difficult for adults than for teenagers, particularly for older persons. Elderly patients tend to have higher rates of surgical complications, longer recovery times, and a greater probability of needing revision procedures.

Investigation 7: What are the limitations of CA measurement?

P.S: The datasets used to train DL models, as well as the models themselves, have a number of limitations, despite the fact that these algorithms can provide automated and effective solutions for CA measurement. Some of the limitations are mentioned below:

a) To achieve good generalisation across various scenarios, DL models need to be trained on large diverse datasets. It can be difficult to get a suitably large and diverse dataset for spine images, though, particularly when it comes to a wide range of age groups, ethnicities, and degrees of spinal abnormalities.

b) The model may not function well on cases that differ from the training data if the dataset used for training is biased towards particular demographics, imaging modalities, or kinds of spinal abnormalities.

c) Measurements of CA frequently depend on manual suggestions made by human observers. The annotation style used by several specialists on the same images can vary significantly. The model's performance may be impacted by noise introduced into the training set by this inconsistent annotation process.

Investigation 8: How can we address these limitations in future research?

P.S: By utilizing DL models and datasets, future research on CA measurement may concentrate on resolving current issues. The following are some suggestions for further study:

a) To ensure that models perform well in a variety of patient groups, build datasets that cover a broad range of demographic variables, including age, gender, and ethnicity.

b) To make sure the model learns to handle a variety of challenging scenarios, include cases with different spinal defects beyond traditional scoliosis.

c) Examine the creation of models that can manage different types of imaging, including CT, MRI, and X-rays. The performance and generalizability of the model may be enhanced by integrating data from other modalities.

VI. CONCLUSION AND FUTURE ASPECTS

Scoliosis detection and CA measurement have evolved significantly over time, from the past to the present, and continue to advance into the future. Scoliosis detection and CA measurement have come a long way, with advancements in technology and medical understanding significantly improving diagnosis and treatment. In this work, we first introduce the general overview of Scoliosis detection and CA measurement. Further, a systematic review has been conducted on Scoliosis detection, and PRISMA guidelines are followed for rigorous analysis. More than 413 articles were collected from this review process, and 44 were selected for the critical analysis. After rigorous analysis, a methodology is proposed with different types of DL models and performance metrics used by the researchers in their work. The various DL approaches for scoliosis detection are then examined, and it has been observed that DL techniques have achieved significant success in the area of vertebra identification.

Further, the combination of advanced imaging techniques, automation, and patient-friendly approaches offers promising avenues for the early detection and management of scoliosis. The future holds exciting prospects, including AI integration, genetic screening, patient-centric care, and regenerative therapies, which promise to enhance the accuracy, accessibility, and effectiveness of scoliosis management. Continued interaction between medical practitioners, researchers, and technologists will make these upcoming advancements possible.

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