Development of Scoliotic Spine Severity Detection using Deep Learning Algorithms

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***Abstract*—According to research conducted by Johns Hopkins' Division of Pediatric Orthopedic Surgery, around three million new instances of Scoliosis are identified each year, with the majority of cases affecting children between the ages of 10 and 12. The current method of diagnosing and treating Scoliosis, which includes spinal injections, back braces, and a variety of other types of surgery, may have resulted in inconsistencies and ineffective treatment by professionals. Other scoliosis diagnosis methods have been developed since the technology's invention. Using Convolutional Neural Network (CNN), this research will integrate an artificial intelligence-assisted method for detecting and classifying Scoliosis illness types. The software model will include an initialization phase, preprocessing the dataset, segmentation of features, performance measurement, and severity classification. The neural network used in this study is U-Net, which was developed specifically for biomedical picture segmentation. It has demonstrated reliable and accurate results, with prediction accuracy reaching 94.42%. As a result, it has been established that employing an algorithm helped by artificial intelligence provides a higher level of accuracy in detecting Scoliosis than manual diagnosis by professionals.**

Keywords—Scoliosis, cobbs' angle, deep learning, CNN, U-Net

I. Introduction

Scoliosis is an abnormal sideways curvature of the spine that most frequently occurs during a child's growth spurt before puberty. Additionally, it can be defined as the presence of one or more lateral curves in the coronal plane of the vertebral column [1]. While most scoliosis cases are mild, several spine deformities may worsen as the child grows. Scoliosis can develop before skeletal maturity, affecting body appearance, cardiopulmonary function, and even paralysis [2]. Additionally, certain forms of Scoliosis can be disabling. For instance, if the spinal curve is completely severe, it can affect the amount of space available in the chest, making it more difficult for the lung to function correctly.

Scoliosis can be disabling in some situations. For instance, if the spinal curve is completely extreme, it can decrease the amount of space available in the chest, impairing the lung's ability to function correctly. The image in Figure 1 depicts a skeleton with severe Scoliosis, highlighting the lungs' reduced space due to rib deformations [3].

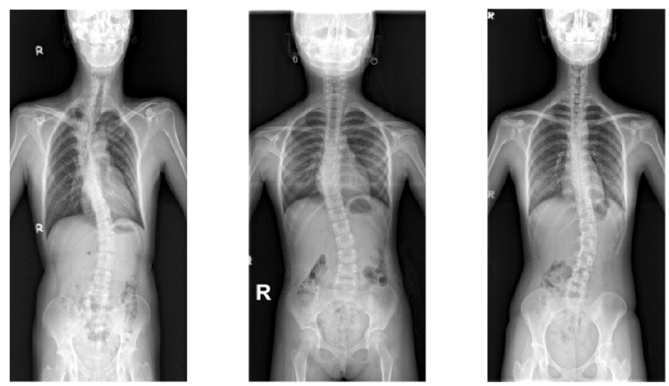

Fig. 1. Sample of Scoliosis X-Ray Images from IIUM Kuantan Hospital

The Cobb angle of the spine is the standard clinical measurement of the severity and alignment of Scoliosis. Cobb angle is defined as the angle formed by two intersecting lines perpendicular to the top and bottom of the vertebrae. Additionally, Scoliosis is not considered when the Cobb angle is less than 10 degrees. Scoliosis is classified as mild when it is between 10 and 20 degrees, moderate when it is between 20 and 40 degrees, and severe when it is greater than 45 degrees. As a result, the greater the Cobb angle, the more severe the condition. The degree of Cobb angle and its classification are listed in Table I.

TABLE I. Cobb Angle and Scoliosis Classification

Degree of Cobb Angle (°)	Classification
<10°	Normal
10° < x < 25°	Mild
25° < x < 45°	Moderate
>45°	Severe

As we all know, Artificial Intelligence (AI) has enormous potential for identifying meaningful relationships within data and can be used in medical diagnosis to forecast the outcome of

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a variety of clinical scenarios [4]. On the other hand, Machine Learning (ML) is a subfield of artificial intelligence responsible for a machine's ability to 'learn.' It addresses how to construct computers capable of automatically improvising based on their prior experience. Additionally, machine learning is predicted to pave the way for enhanced healthcare in the future by unlocking the potential of enormous biological and patient datasets [5]. In simple terms, machine learning operates to improve machines' ability to perform specific tasks given a dataset or based on prior experience. AI can assist in this process by helping in the diagnostic interpretation of X-ray, magnetic resonance (MR), and computed tomography (CT) images, preventing illness indications from being overlooked. More precisely, AI is intended to automate the diagnosis of metastatic cancers and vertebral fractures in the spine.

II. Related Works

Numerous medical studies have used AI to improve the identification of Cobb angle in Scoliosis. These studies demonstrate the adaptability of AI and its impact on the medical system. Watanabe et al. [6] created a method to assess spinal alignment from moiré images using Convolutional Neural Network (CNN). Insufficient sensor resolution causes moiré patterning in photographs. The students' moiré photos screened resulted in 10,788 pairs of moiré images and standing whole-spine radiographs. They meticulously marked the position of vertebral bodies and four landmarks on both sides of the waist and neck. AlexNet is used to forecast the locations of 17 vertebral bodies, and specialists compare the findings. Averaging 3.42 degrees between experts and researchers, the researchers observed that the mean absolute error (MAE) from computed cobb angles using CNN and moiré pictures was similar to 3.42 degrees. However, the system's precision is sensitive to physician image interpretation training. The quality of picture evaluation and the instrument's performance also limit image acquisition.

The traditional Cobb angle measurement method is flawed by high interobserver and intraobserver error ranging from 3 to 10 degrees, according to Bernstein et al. [7]. A spline made from vertebral centroids was used to simulate the curved spine's features closely. The team also uses U-Net, an established technique in medical imaging segmentation, to automatically find centroids. The U-Net uses skip links between encoder/decoder structures to retain data over multiple CNN layers. Masked loss functions that grip penalized places are introduced outside the spine to improve the output. This study's primary goal is to improve the technique's precision at no extra cost. The results show that splines have a higher interobserver correlation ranging from 0.92 to 0.95 than manual Cobb angle measurements ranging from 0.83 to 0.92. CNN application showed superior precision mean deviations of less than 0.5 degrees. The findings suggest that the higher thoracic spine is questionable. The dataset of spinal X-ray imaging must also be modified to improve picture recognition.

Next, Papaliodis et al. [8] enhanced Cobb angle measuring utilizing a novel PACS method that eliminates the need for goniometers. However, the strategy has not improved inter-and intraobserver precision. Thus, the researchers use Bonanni's computer-aided technique to estimate the Cobb angle from coronal spine scans using composite structural curves (CSC). An initial estimation was made using a visual matching process when the deviation was noticed. Using a computer-aided technique, the study assessed 58 PA radiographs and compared the results to formulated values. The computer-based approach determined Cobb's angles within 5 degrees of the trained orthopedic expert's mean average. The study confirmed the algorithm's dependability and accuracy; however, the study's drawback is the pre-designation of spinal levels, which is determined by the medical practitioner's initial judgment.

Similarly, Zhang et al. reported in 2015 [9] that using a computer-aided technique could help detect the Cobb angle in Scoliosis. The method is based on King classification, where it can define five types of the curve and improve the 'miscellaneous' from the measurement of standing coronal radiographs. The study used 105 PA radiographs of scoliotic patients with five observers: an orthopedic surgeon, an orthopedic resident, a medical student, a radiologist, and a software engineer. First, the Central Sacral Vertical Line (CSVL), Cobb angle, and apical end vertebrae positions are established. Spinal malformation was classified into five forms. The lumbar curve is larger than the thoracic curve in Type I and II. In Type III, the lumbar curve does not cross the CSVL, while Type IV and V have no lumbar curve. The kappa statistic (κ) was employed to assess the study's reliability. The study results showed that the five observers' values κ ranged from 0.88 to 0.93, which is outstanding. The data reveals that the average κ value increases from 0.82 to 0.90. Thus, the proposed automated King categorization system may be a helpful aid in reducing Cobb measurement variability and human judgment errors. Before the computerized classification method can be used, the user must manually set the Region of Interest (ROI) and identify the prominent landmarks.

X-rays or MRIs are the most common methods for measuring the spine. However, these treatments increased patients' radiation exposure. Wu et al. [10] introduce the scoliosis screening approach using a portable ultrasound machine. The technique detects the transverse spinal process using CNN in ultrasonography. They used 2752 ultrasound images to train the CNN and 747 images to test it. 3D slicer is used to segment all ultrasound pictures from scans manually. Inception v1 (GoogleNet) has 22 layers and nine modules, with 1×1, 3×3, and 5×5 operating filters at the same level. The outputs were concatenated and sent to the inception module. The Inception CNN detected spinal processes with an accuracy of 84% in the study. Although adding additional data to the classification model could improve accuracy, the use of CNN in spinal detection and categorization of ultrasound images was reliable and accurate.

Pan et al. [11] have investigated the use of Mask R-CNN models to compute Cobb angle and identify Scoliosis using chest X-rays. 248 X-ray images of lung cancer patients were used to locate and segment the spine of vertebral bodies. The inferior and superior endplates of each vertebral frame are also determined using Mask R-CNN models. The Cobb angles were calculated using a computer-aided procedure, and two expert radiologists manually compared the findings. According to the observation reports, the intraclass correlation coefficients (ICC) of intraobserver and interobserver accuracy of the analysis were

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0.941 and 0.887, respectively. The ICC between manual and computer-aided procedures is 0.854, with a MAD of 3.32 degrees. Thus, the computer-aided method was reliable for determining the Cobb angle on chest X-rays. However, this method has certain drawbacks, including that CNN only analyses the uppermost angle between the superior perpendicular of cranial vertebrae and the inferior perpendicular of caudal vertebrae. For greater performance, the CNN needs to be trained with a larger dataset than the typical radiographs of the spinal curves. Finally, the study was an early evaluation of the computer-aided method, and more research is needed to improve the findings.

On the other hand, Horng et al. [12] suggested an automatic approach to estimating spine curvature using anteroposterior (AP) X-ray images. The system uses U-Net, Dense U-Net, and Residual U-Net deep learning CNN for vertebrae segmentation and Cobb angle computation. This study used 35 AP view spinal X-ray pictures as a dataset. The segmentation findings of the Residual U-Net managed to deliver the highest accuracy compared to the others, with an average Dice similarity coefficient of 0.951. Residual U-Net design had 96.9% accuracy compared to 96.1 % for U-Net and 96.6 % for Dense U-Net. This algorithm's ICC was 0.94, compared to the expert's ICC of 0.936. The ICC and Pearson correlation coefficients are above 0.93, indicating that the results closely match the manual assessment. This system's flaw is that it just computes the Cobb angle rather than detecting and classifying the types.

III. DEVELOPMENT OF COBB ANGLE DETECTION IN SCOLIOSIS

To develop the system's approach and implementation, a deep learning algorithm based on CNN will be used to train the data and classify the images according to their severity class. The proposed algorithm's general flow is depicted in Figure 2. The procedure can be broken down into four distinct stages: startup, vertebrae segmentation, performance evaluation, and severity categorization.

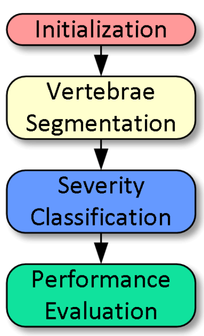

Fig. 2. Severity Classification on Scoliosis Images

A. Initialization

This data pre-processing aims to improve the algorithm's capacity to detect important information and remove any undesirable noise or distortion in the image. It is critical because it will significantly impact the project's outcome. The data input for the initialization stage will be the spinal anterior-posterior X-ray images. Each image labeled with ground truth will be examined, and any detected inaccuracies will be fixed. This stage will also include the isolation of the spine's ROI. The example of a scoliotic X-ray image and its ROI can be seen in Fig. 3.

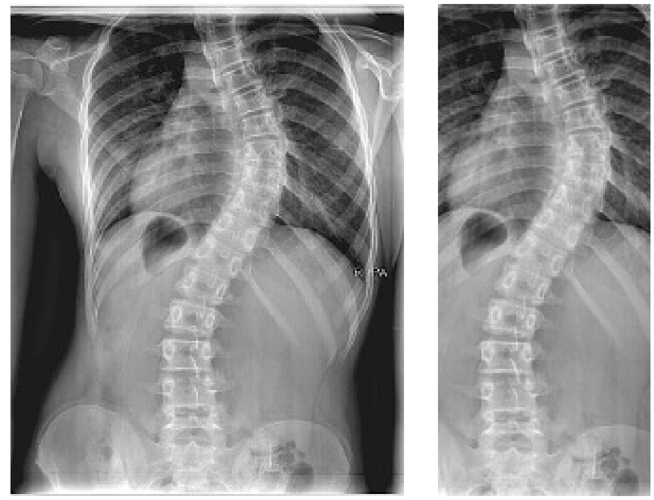

Fig. 3. Sample of Spinal AP X-Ray Image and its ROI.

B. Vertebrae Segmentation

After the spine region is extracted, the vertebrae detection stage is performed. In general, the spine appears brighter within the cropped spine ROI. Thus, the spine's corners and borders will be easier to detect by locating the image's white pixels. Using this method, masks for neural network testing and training data can be constructed using Matlab's image processing library to detect the white pixels in images. The masks developed are critical in assisting the algorithm in determining the vertebrae's position in the spine. Additionally, the masks are employed for the algorithm's learning function during data training. Using the trained neural network, each vertebra on the spine can be delineated and plotted on the original ROI. The fitted endplates of the vertebrae may then be produced and plotted on the original pictures using the vertebral outline for each sample. Each of the fitted endplates is calculated from vertebrae outline using the algorithm in Matlab, and they are the critical elements in the next transition, which is to obtain the Cobb angle value. The Cobb angle is calculated using the software's algorithm based on the fitted endplates. Each curve will automatically mark the most twisted upper and lower vertebrae to determine the Cobb angle values.

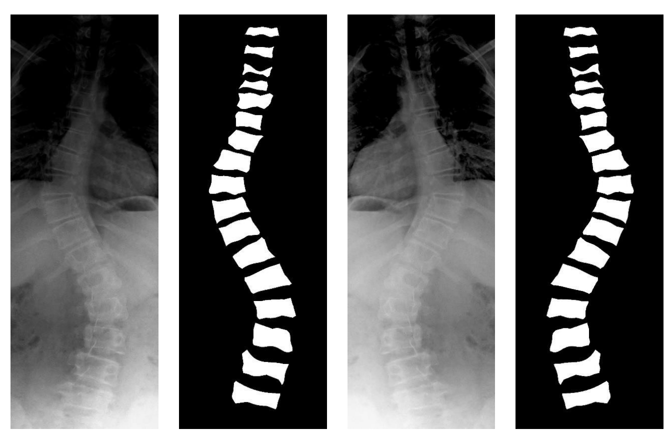

Fig. 4. Sample of Spinal AP X-Ray Images and Its Masks.

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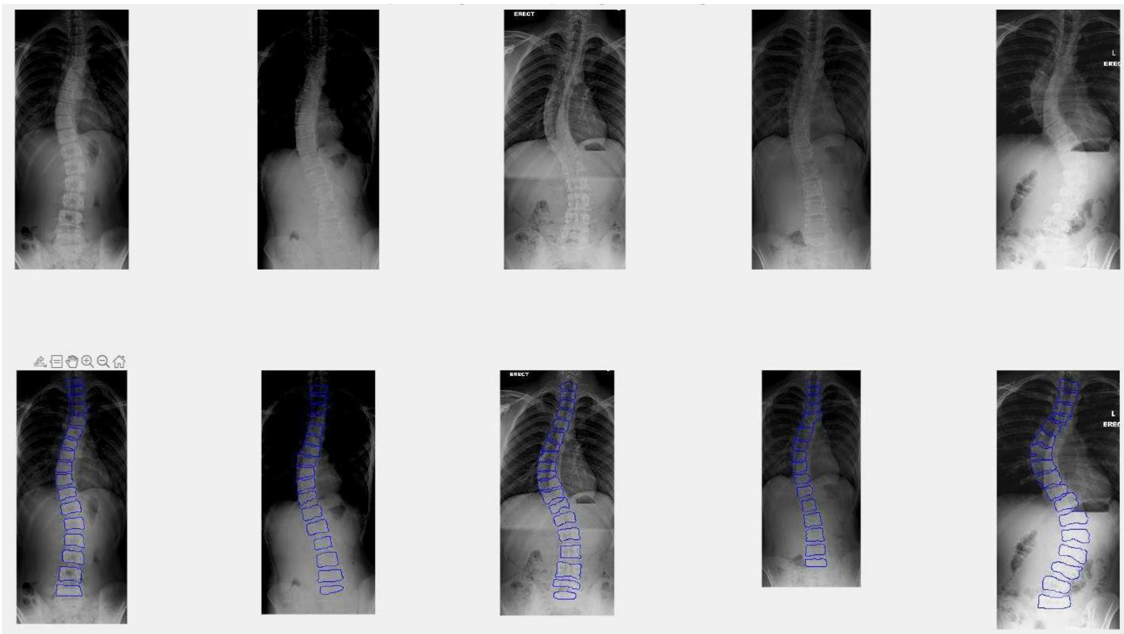

Fig. 5. Sample of X-ray Images and Its Vertebrae Segmentation

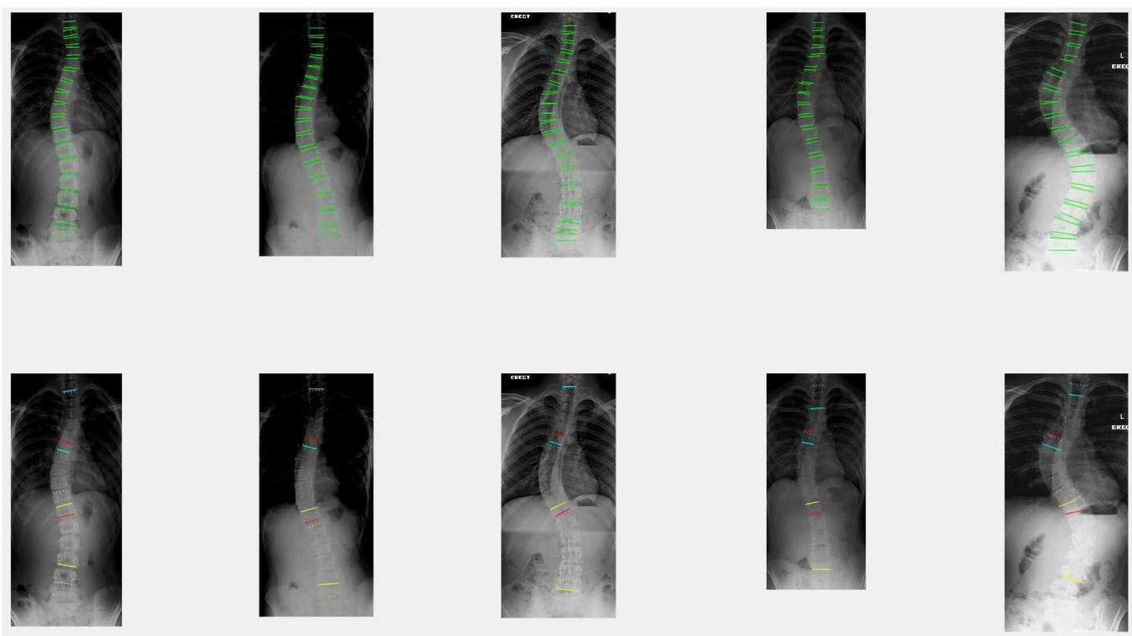

Fig. 6. Endplates and Its Corresponding Cobb Angles

Figure 4 illustrates the masks produced from the X-ray images. The vertebral segmentation, endplates, and Cobb angles are illustrated in Figures 5 and 6, respectively.

C. *Severity Classification*

The Lenke classification will be used to identify the vertebrae's severity classifications in this step. Additionally, it is a triad categorization approach comprised of curve type analysis, lumbar spine modifier analysis, and sagittal thoracic modifier analysis. This classification system is exhaustive, dependable, practical, and used by Scoliosis surgeons.

TABLE II. CLASSIFICATION OF SPINE REGION

Region	Location of vertebrae
Proximal thoracic	Apex at T3, T4 or T5
Main thoracic	Apex between T6 and the T11-T12 disc
Thoracolumbar/Lumbar	Thoracolumbar apex between T12 and L1 Lumbar apex between L1-L2 disc and L4

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To begin, we shall divide the spine into three regions, as indicated in Table II. Cobb angles are then calculated from cranial to caudal end vertebrae in AP view. The end vertebra is positioned at the highest angled angle from the horizontal apical vertebra. The major curve is defined as the curve with the greatest Cobb angle. The cranial end and caudal end vertebrae are depicted in Figure 7.

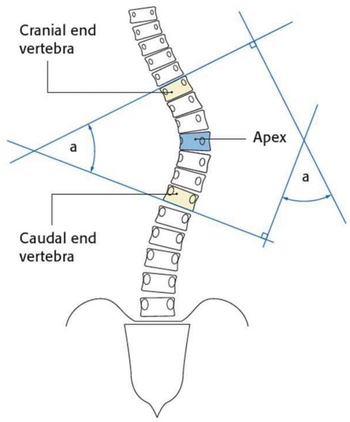

Fig. 7. Cobb Angle Measurement Area Adopted from [13]

D. Performance Evaluation

The network's performance will be evaluated in this step based on the accuracy with which the neural network detects and classifies the vertebrae. The evaluation will be based on the correlation between the system's actual and projected values. Additionally, the performances are investigated further by spreading the data from the results into a normal distribution graph to determine the neural network's overall correctness.

In other words, all data were entered to construct a normal distribution plot, which was used to determine the probability of data correctness given the ground truth and expected values. The ground truth values are determined manually by specialists, whereas the system determines the anticipated values. Additionally, a scatter plot will be created to illustrate the relationship between the true Cobb angle and the anticipated Cobb angle. This stage is critical for determining whether the proposed algorithm correctly distinguishes and matches the data from the ground truth and the expected data.

E. Implementation

U-Net will be employed as a convolutional neural network in this project, which will be included in the detection method. U-Net was explicitly developed for biomedical image segmentation, and its architecture was modified and enhanced to enable it to function with fewer training images and provide more exact segmentation. The major alteration to this CNN is that the up-sampling portion now has more feature channels, allowing for the transmission of network information into higher resolution layers. As a result, the expansive path appears to be symmetrical with the contracting segment, resulting in a u-shaped design. Additionally, this network utilizes only a good portion of each convolution, excluding any fully connected layers [14]. Figure 8 summarizes the U-Net architecture for scoliosis detection, especially on the vertebrate segmentation part.

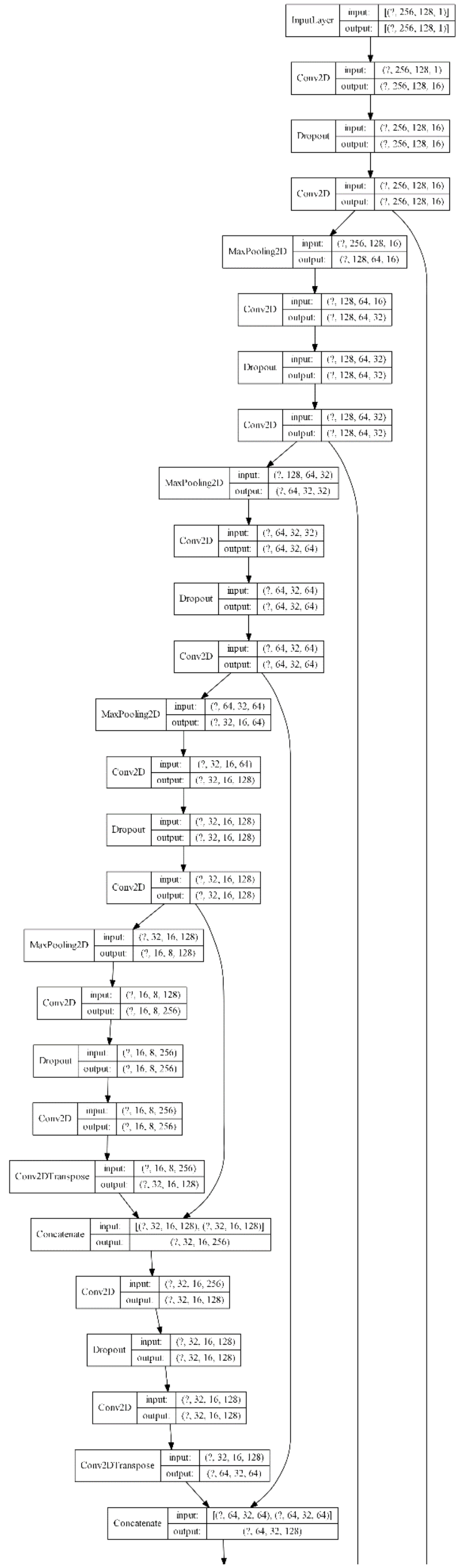

Fig. 8. Half Part of U-Net Architecture

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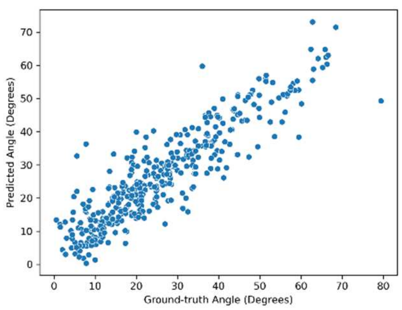
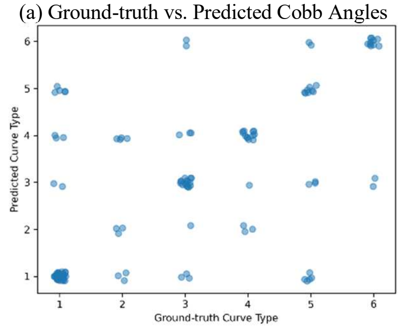
IV. Results and Discussion

The results in this part will be based on the algorithm method proposed for detecting Scoliosis using U-Nets, and the dataset provided in [15], which has 609 AP X-ray images. Rather than manually measuring the Cobb angle, the algorithm will automatically segment the vertebrae, locate fitting endplates, and calculate the Cobb angle to predict the probability of curve type based on the x-ray pictures. The algorithm will classify the data using the Lenke classification scheme based on the various Cobb angles found. Furthermore, the ground truth and predicted values are compared using a scatter plot to validate the relationship between the two variables, as shown in Figure 9. The algorithm is implemented on a computer with Ryzen 7 3700X, 32 GB RAM, and GPU RTX 3070. The U-Net deep learning model was using Adam optimizer with Tversky loss function. It was trained for 200 epochs, in which the total training time is 43 minutes.



(a) Ground-truth vs. Predicted Cobb Angles



(b) Ground-truth vs. Predicted Curve Types using Lenke Classification

Fig. 9. Ground-truth vs Predicted Cobb and Curve Types

The training and validation accuracy was recorded as 95.88% and 94.42%, respectively. The correlation coefficient for Cobb angles and Lenke classification were 0.903 and 0.769, respectively. Furthermore, the Intraclass Correlation Coefficient (ICC) for Cobb angles and Lenke classification were 0.948 and 0.869, respectively. Results showed that our proposed algorithm can predict the Cobb angles with good accuracy, while the Lenke classification can be improved further.

V. Conclusions and Future Works

Scoliosis identification using deep neural networks requires multiple stages to generate an efficient mask for network training based on the created landmarks coordinate file. The model is composed of the initialization, vertebrae segmentation, classification of curve severity The model's use of the U-Net deep learning architecture achieves a dependable and accurate result of 94.42% accuracy in detecting the Cobb angle for Scoliosis diagnosis. Future research will use a variety of deep learning architectures, including Residual U-Net and Dense U-Net, as well as additional Scoliosis X-ray imaging datasets.

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