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Machine Learning Approach for Detection and Classification of Scoliosis in Human Bones from X-Ray Images

Taoheed A. ADEYANJU[1*], Tokunbo JOHNSON[2], Isaac G. KOLAWOLE[3]

[1]*Department of Computer Engineering, University of Uyo, Uyo, Nigeria (9 pt size, italic)*
[2]*Department of Agricultural Engineering, University of Abuja, Abuja, Nigeria (9 pt size, italic)*

[1*]*adebayoadeyanju865@gmail.com*, [2]*jtoks2011@gmal.com*, [3]*kolaisaac96@gmail.com*

Abstract

Scoliosis is a prevalent orthopedic condition that affects individuals across various age groups. It is a lateral curvature of the spine and its early detection is crucial for effective treatment of the condition. This study presented a machine learning based model for detection and classification of scoliosis from X-ray images. A total of 261 X-ray images depicting the spine in posterior-anterior and lateral views which consisted of 189 positive scoliosis cases and 72 negative cases forming datasets for the study were curated from Yaba Gbobi hospital and online zip extractor. Data analysis via the use of descriptive statistics such as mean, standard deviation, minimum and maximum pixel intensities was done to extract the image properties. Data pre- processing involved resizing of the images to a standardized dimension of 224 mm x 224 mm was carried out. Augmentation of the dataset was done using Fast Artificial Intelligence (fast AI) codes written in Python Programming Language, by setting up image data loaders from folders to path to dataset which trained and validated the images selected in batches from the dataset. The model was trained using a Convolutional Neural Network (CNN) architecture (VGG 16- an object detection and classification algorithm) which was able to classify images of different categories with high accuracy. The model's hyper- parameters such as learning rate, batch size and the number of layers were tuned with grid search and random search techniques. The performance of the model was evaluated with the application of the Sci-learn to determine the: accuracy, precision, recall and F1 score. The obtained values were compared with the existing baseline method of measuring the degree of scoliosis curve (Cobb angle) in recent times such as the use of measuring ruler. The results obtained revealed that the model achieved higher accuracy, precision, recall and F1 score of 88.23, 89.84, 86.95 and 88.49%, respectively, compared with existing baseline method of lower accuracy, precision, recall and F1 score of 80.12, 82.55, 81.55 and80.00%, respectively. The model produced predictive outputs in the form of probabilities or confidence scores for each input X-ray image with the higher scores indicated a higher probability of scoliosis, while lower scores suggested a lower likelihood. These collectively demonstrated the model's balanced performance in identifying scoliosis cases while minimizing false positives and false negatives. The model's precision ensured accurate positive predictions, while high recall ensured effective detection of actual scoliosis cases. The machine learning based model detected and classified scoliosis from X-ray images.

Keywords: *Machine Learning, Scoliosis, X-ray Images, Classification.*

1.0 Introduction (10 pt size, bold)

The vertebra column or spine is an essential segment of the vertebrate animal skeleton. It acts as the fulcrum of human body and consists of a number of interlocking vertebrae responsible for flexibility and structural support in the performance of physical activities ranging from simple actions such as twisting and bending to walking and running which are more complex (Lu and Nguyen, 2024; Maaliw , 2023; Fraiwan *et al.*, 2022; Mahesh *et al.*, 2022). This signifies the importance of the vertebra column (VC) to the overall functionality of the human body. In the modern human life cycle which is more demanding as a result of various day-to-day activities, the VC is affected by different diseases and one of the foremost in this regard is scoliosis (Gunes *et al.*, 2024; Lu and Nguyen, 2024; Fraiwan *et al.*, 2022; Alharbi *et al.*, 2020).

Scoliosis refers to the spinal deformity which is characterized by lateral curvature and rotation of the VC (Kumar *et al.*, 2024; Zhang *et al.*, 2023; Ha *et al.*, 2022; Mahesh, 2022; Tajdari *et al.*, 2021). It is a medical condition which presents significant healthcare challenges impacting millions of people globally, particularly during adolescence, a critical period of growth and development (Maaliw , 2023; Caesarendra *et al.*, 2022; Murray *et al.*, 2021; Tajdari *et al.*, 2021). Scoliosis can appear at any age and its progressive nature can result in asymmetry not only in the rib cage and shoulders but also in other organs of the body such as lungs and heart which are vital to human existence (Zhang *et al.*, 2023; Fraiwan *et al.*, 2022; Konieczny, *et al.*, 2013).

According to Fabijan *et al.,* (2023), scoliosis can be classified based on many criteria including cause, age of onset, curvature pattern, location, and severity. However, three key forms of the condition which are idiopathic, congenital, and neuromuscular exist (Zhang *et al.,*, 2023; Alharbi *et al.,*, 2020). Idiopathic scoliosis is the commonest and occurs in a healthy child with no known cause or specific factor that aids its progress. Congenital scoliosis is a defect of the spine associated with birth and this makes its early detection much easier. Neuromuscular scoliosis is a spinal abnormality prompted by the neurological or muscular disease (Alharbi *et al.,*, 2020). All these forms of scoliosis require prompt intervention to de-escalate the progression of the condition. Hence, early diagnosis and treatment become a necessity to improve the quality of life of the patients.

Currently, the scoliosis diagnostic methodologies in use heavily rely on visual examination by radiography physicians and/or measurement of certain angles such as the Cobb angle (Fraiwan *et al.,*, 2022). These approaches are inherently prone to biases, subjectivity and inter-observer variability (Maaliw, 2023; Kim, *et al.,*, 2015). This, therefore, paves way for more advanced techniques involving the use of artificial intelligence (AI). Conventional AI based diagnosis systems employed visual inspection and Cobb angle to execute automated classification which facilitates easy and quick diagnosis of scoliosis. However, the involvement of the specialists to perform error-prone analysis remains a major limitation (Fraiwan *et al.,*, 2022). Hence, the need for more sophisticated AI based techniques such as machine learning (ML) which can enable fully automated measurement is evident.

One of the pathological conditions that negatively impact the VC which provides mobility and stability in human body is scoliosis (Costa *et al.,*, 2023; Petrosyan *et al.,*, 2023). This medical condition generally has a prevalence of 0.47-5.2% of the population depending on the country (Fraiwan *et al.,*, 2022). Scoliosis can significantly alter the body posture resulting in severe pain, discomfort and paralysis in extreme cases when left unattended to (Kumar *et al.,*, 2024; Maaliw, 2023). Early detection and treatment is, therefore, necessary to halt its progression.

The manual methods currently deployed for scoliosis diagnosis have been reported to be time-consuming, laborious and subjective to the experience of the physicians of radiographs (Berlin *et al.,*, 2023; Liu *et al.,*, 2022). These in essence are deleterious to effective assessment of the relevant parameters which are crucial in scoliosis analysis for clinical routine and research purposes. Consequently, there is a pressing need for more objective and efficient approaches to automate scoliosis detection and classification from X-ray images, leveraging emerging technologies such as ML which uses algorithms and machines to identify patterns from large datasets to extract vital information. The development and implementation of ML- based diagnostic systems in the spine field can enormously assist in identifying patterns in scoliosis diagnostic data which were previously undiscovered for effective treatment of the condition (Chen *et al.,*, 2021). Therefore, this research employed a ML model for detection and classification of scoliosis in human bones from X-ray images.

Recent strides in medical imaging technologies and the burgeoning field of ML technology have ushered in promising avenues for automating the detection and classification of scoliosis from X-ray images, potentially heralding a transformative shift in the current diagnostic paradigms (Zhang *et al.,*, 2023; Chen *et al.,*, 2021; Sung, *et al.,*, 2021). These advancements offer unprecedented opportunities to harness the power of computational algorithms and large-scale datasets of annotated X-ray images to develop robust and efficient automated systems capable of accurately discerning and categorizing spinal deformities with unparalleled speed, precision, and scalability, thereby enhancing diagnostic accuracy and facilitating timely clinical interventions. Therefore, the goal of this research was to use fast AI framework which is a ML model for detection and classification of scoliosis in human bones from X-ray images.

The aim of this research is to detect and classify scoliosis in human bones from X-ray images using ML approach.

1.2 Literature Review

Scoliosis is defined by the Cobb's angle of spine curvature in the coronal plane and is often accompanied by vertebral rotation in the transverse plane and hypokyphosis in the sagittal plane (Sung, *et al.,*, 2021).

Scoliosis can appear at any age but it is most common in the later stages of childhood or the early teenage years when the person is still growing fast. It often presents itself between the ages of 10 and 12 years or during age of teenager. Scoliosis is rare in infants, infantile scoliosis can affect people before the age of 3 years. Alternatively, it may be a birth abnormality. It is more common in females than in males. Scoliosis is not always noticeable, but some people with this condition may lean to one side or have uneven shoulders or hips due to the curve of the spine.

In most cases, the person does not need treatment because the curve often does not progressa significant amount. However, depending on the degree of curvature and the age of the child, doctors may recommend a combination of back bracing and physical therapy. A very small number of people with scoliosis may need

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surgery. Possible complications of scoliosis include chronic pain, breathing difficulties, and a reduced capacity for exercise

Scoliosis can be classified according to its aetiology or its location. Classification by location is as follows: cervical, cervicothoracic, thoracic, thoracolumbar, lumbar, lumbosacral. The more accepted method of classification is the aetiological classification of scoliosis that is subdivided into two categories namely structural and nonstructural (functional).

Structural scoliosis: In this group of scoliosis, the spine is not anatomically normal and the deformity is caused by the influence of various internal and external factors or by another disease and is usually irreversible (Malfair, *et al.,*, 2010). The spine not only curves from side to side, but the vertebrae also rotate, twisting the spine. As it twists, one side of the rib cage is pushed outward so that the spaces between the ribs widen and the shoulder blade protrudes (producing the rib-cage deformity, or hump); the other half of the rib cage is twisted inward,

compressing the ribs (Da Silva, *et al.,*, 2010).This group includes: idiopathic scoliosis, congenital scoliosis, neuromuscular scoliosis, neurofibromatosis, rheumatic diseases, trauma, contractures, osteochondrodystrophy, bone infections, metabolic disorders, tumors, mesenchymal disorders (Ehfan-marfan syndrome, etc.).

Direction of the curve in structural scoliosis is determined by whether the convex (rounded)side of the curve bends to the right or left (Tu, *et al.,*, 2019). For example, a physician defines a certain case as right thoracic scoliosis if the apical vertebra is in the thoracic (upper back) region of the spin and the curve bends to the right. The magnitude of the curveis determined by taking measurements of the length and angle of the curve on an x-ray view.

Nonstructural Scoliosis: The type of scoliosis is a temporary (reversible) condition where the spine is normal and the deformity results from another problem. A nonstructural curve does not twist but is a simple side-to-side curve (Wang, *et al.,*, 2021). Other abnormalities of the spine that may occur alone or in combination with scoliosis include kyphosis (an exaggerated backward rounding of the spine, the so-called hunchback) and hyperlordosis (an exaggerated forward curving of the lower spine, also called swayback) (Fujimori, *et al.,*, 2022). The physician attempts to define scoliosis by the location, direction, and magnitude of the curve, and, if possible, its cause. The location of a structural curve is determined by the particular apical vertebra, the bone at the apex, or highest point, in the rib cage hump; this particular vertebra will also have undergone the most severe rotation. This group includes: postural scoliosis, hysterical scoliosis, scoliosis due to irritation of nerve roots, discrepancies in the length of the lower extremities, shortening of the lower extremity infections and inflammations of the abdominal region (e.g. appendicitis) or spine.

The severity of scoliosis depends on the degree of the curvature and how much it threatens vital organs, specifically the lungs and heart. Leveraging on these,scoliosis is classified as follows:

Mild Scoliosis **-** Mild scoliosis is categorized to have less 20 degrees and requires no treatment. It possesses no significant effect on the organs of the body excluding the affected posterior region.

Moderate Scoliosis - Moderate Scoliosis is considered to have a cobb angle degree of between 25 and 70 degrees (Zhou, *et al.,*, 2023). It is not clear whether moderate scoliosis causes significant health problems. In Zheng, *et al.,*, *(*2016), adults with moderate scoliosis had normal lung function, although they had difficulty exercising. The researchers believed that this low exercise tolerance might have been because manypatients with scoliosis do not engage in regular physical activity.

The number of patients will increase every year for 250,000 new patients and sometime in 2050, there will be approximately 36 million patients with scoliosis, with majority of cases being idiopathic scoliosis. The AIS develops at the age of 11-18 years and accounts for a major part of the idiopathic scoliosis (Mahesh, *et al.,*, 2022). The prevalence of adolescent idiopathic scoliosis affects more women than men and this ratio increases in favour of women with increasing age. Every year, scoliosis patients make more than 600,000 visits toprivate physician offices, an estimated 30,000 children are fitted with a brace and 38,000 patients undergo spinal fusion surgery.

There are several signs that may indicate the possibility of scoliosis. These are sideways curvature of the spine, sideways body posture, one shoulder raised higher than the other, clothes not hanging properly, local muscular aches, local ligament pain and decreasing pulmonary function, major concern in progressive severe scoliosis.

In a recent study by Qiu *et al.,* (2009), about 75 percent of patients with idiopathic scoliosis presented with back pain at the time of initial diagnosis. 25.3% percent of these patients were found to have an underlying associated condition such as spondylolisthesis, syringomyelia, tethered cord, herniated disc or spinal tumor. If a patient with diagnosed idiopathic scoliosis has more than mild back discomfort, a thorough evaluation for another causes of pain is usually advised by the doctor (Lincoln, 2007).

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Due to the changes in the shape and size of the thorax, idiopathic scoliosis may affect pulmonary function (Tajdari, 2021). Recent reports on pulmonary function testing in patients with mild to moderate idiopathic scoliosis showed diminished pulmonary function. Impairment of function was seen in more severe cases of deformity, proximally-located curvature and older patients (Kim, *et al.,*, 2020).

Alharbi *et al.,* (2020). The research was on deep learning based algorithm for automatic scoliosis angle measurement. Deep convolutional neural network (CNN) were applied to detect vertebra in each X-ray image collected. The cobb angle was measured through a novel algorithm using trigonometry. The proposed method was evaluated on X-rays dataset which detected each vertebra in the images. The method achieved the estimation of cobb angle with high accuracy. The method did not show great potential for clinical use compared with the technique used in this research.

Adibatti *et al.,* (2023). The research was based on design and performance analysis of cobb angle measurement from X-ray images. A curve-fitting approach was used to find the polynomial derivative of a spine inclination. The sample was gathered using different acquired radiography. The curve-fitting approach used the median as a raw dataset and least squares techniques were used to create a numerical solution. The method did not give room for classification of scoliosis for medical intervention unlike the technique used in this research.

Pavani *et al.,* (2023). The research detected Adolescent Idiopathic Scoliosis using a novel machine learning approach. Demographic and Radiographic measurements, including coronal cobb angle were collected into two different databases. Cobb angles for each affected spine were calculated to measure the angular difference between the normal spine and the abnormal spine. Naïve Bayes classifier was used in predicting whether a person had scoliosis or not. Performance metrics were calculated against Naïve Bayes to calculate the accuracy of positive or negative prediction of scoliosis disease. After pre-processing, the image database was extracted using Scale Space Extreme Detection. In the method, only cobb angle for specific region and demographic data were known. The method used in this research detected scoliosis beyond specific region and demographic data.

Suri *et al.,* (2023). The research was on deep learning automated hardware invariant measurement of cobb angle on radiographs in patients with scoliosis. A neural network architecture was designed to perform two tasks; to detect vertebral bodies and to locate the four corner points on each vertebral body. The network architecture called spine TK, was used in the task of vertebral deformity quantification and was retrained for the purpose cobb angle measurement. The method did not give better accuracy as compared with fast AI method used in this research.

Gou *et al.,* (2024). The research investigated the biomechanical differences in trunk and lower limbs during daily stair activities between patients with scoliosis and a healthy population. Data collection was done through Qualisys system. It captured the kinematics of the lower limbs as well as the kinetics of the lower limbs during stair ascent and descent for both individuals with scoliosis and control participants using V3D software (Vision3D). The V3D software's model based calculation function was employed to determine the joint angles. A three-dimensional coordinate system was established for each segment around each coordinate axis were obtained. The findings did not encompass all aspect of scoliosis as compared with the technique used in this research.

Guanche *et al.,* (2024). The thesis focused on the role of deep learning in the detection and treatment of scoliosis. The data collected undergo a first pass examination which exclude patients whose treatment hadto be interrupted. A second pass examination was conducted to determine that all data points amongst the three groups collected. For the cobb angle measurements, a statistical analysis consisting of the mean differences, Pearson Correlation Coefficient and Lin's Concordance Correlation Coefficients were used to compare the cobb angle measured by orthopedic experts to the individual Deep Learning algorithm used. The limitation of the work was that the pre-training for predicting likelihood of progressive diseases with ImageNet was not standardized nor validated unlike the framework used in this research.

Gunes *et al.,* (2024). The research classified spine X –ray images in three possible conditions (Normal, Scoliosis and Spondylolisthesis) in other to detect possible diseases occurring in the spine. Six different deep learning architectures were used to include Alexnet. Evaluation of the learning model was done using RmsProp optimization algorithms and very high accuracy was achieved in the detection of the medical conditions. The method did not really detect scoliosis in spine as compared to the method used in this research.

Kumar *et al.,* (2024). The study analysed scoliosis detection by vertebra identification and cobb angle estimation using deep learning techniques. Dataset that denoted the existence and degree of scoliosis were collected and fed into U-Net architecture. Depending on the dataset and available computing ability, the number of layers, filters and hyperparameter were modified. The training on the U-Net model was done on the training dataset using an optimizer like Adam. Evaluation measures such as accuracy, precision, recall

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and F1- score were used. The method did not give avenue for early detection and management of scoliosis as compared with the AI method used in this research.

The earlier methods used did not give avenue for early detection, management of scoliosis and better accuracy as compared with the fast AI method used in this research. Aside good accuracy of this method, it gives room for classification of scoliosis for medical intervention and it shows great potential for clinical use.

2.0 Materials and Methods

2.1 Data set

The dataset used in this study comprises X-ray images of the spine in the Posterior-Anterior (PA) and lateral views. It consists of a total of 261 images, including both positive and negative cases of scoliosis. The X-ray images were collected from a diverse population of patients who underwent diagnostic examinations for scoliosis. The dataset includes images from patients of different age groups, genders, and ethnicities to ensure a representative sample. The images were acquired using standard clinical protocols and equipment.

To maintain data integrity and ensure accurate labeling, an experienced team of radiologists reviewed and annotated each image for the presence or absence of scoliosis. The annotations were made based on visual examination and clinical criteria established by medical experts. The dataset provides a balanced representation of positive (scoliosis present) and negative (scoliosis absent) cases, with approximately 189 positive images and 72 negative images. This balanced distribution enables the development of a robust model for scoliosis detection and diagnosis. It is important to note that patient privacy and ethical considerations were strictly adhered to during the data collection process. All images were de-identified and anonymized to remove any personally identifiable information, ensuring compliance with relevant data protection regulations and ethical guidelines.

2.2 Data Collection and Description

X-ray images were collected from a local hospital's radiology department Igbobi, Yaba and online zip extractor. Approval was also obtained from the hospital's institutional review board to collect these images for research purposes. The X-ray images of the spine were from patients who had been diagnosed with scoliosis as well as images of the spine from patients who had not been diagnosed with scoliosis. The images were anonymized to protect the privacy of the patients. Preprocessing steps, such as image cropping and resizing, to standardize the images were performed. Then, each image was labeled with the degree of curvature of the spine.

2.3 Data Analysis

Before proceeding with the development of the scoliosis detection model, a thorough analysis of the dataset was conducted to gain insights into its characteristics and identify any potential challenges or patterns. The data analysis process involved examining the distribution of classes, exploring the image properties, and performing statistical analysis. This subsection provides a detailed overview of the data analysis conducted on the dataset.

2.4 Class Distribution

The first step in the data analysis was to examine the distribution of positive and negative cases within the dataset. This analysis helps to understand the balance between the two classes and assess any class imbalance issues that may affect the model's performance. The class distribution was calculated by counting the number of positive and negative samples in the dataset. The class distribution was analyzed using the `dls.show_batch` function, which provides a visual representation of the data. Additionally, the `dls.categorize` attribute was used to obtain the class labels and their corresponding frequencies. The code snippet format that was used in analyzing class distribution using FAST AI is described as follows:

 # Load the data and create a DataLoaders object

dls = ImageDataLoaders.from_folder(path, train='train', valid='valid', item_tfms=Resize(224)) # Show a batch of data to visualize class distribution dls.show_batch()

 # Get the class labels and their frequencies class_labels = dls.categorize class_counts = dls.dataset.categorize

The `dls.show batch` function displays a batch of images along with their corresponding labels, providing an intuitive representation of the class distribution in the dataset. To obtain the class labels and their frequencies, the `dls.categorize` attribute returns the list of class labels, and the `dls.dataset.categorize` attribute provides the corresponding frequency counts. These values can be used to analyze the class distribution and assess any class imbalance issues that may need to be addressed during model training. It is worth noting that the specific implementation may vary depending on the dataset structure and the version of the FAST AI library being used. The above code snippet serves as a general guideline for analyzing class distribution using FAST AI.

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2.4 Image Properties

To gain insights into the properties of the X-ray images, several image characteristics were analyzed. These characteristics include image size, color space, and pixel intensity distribution. The image size analysis involved examining the dimensions of the images, ensuring consistency and identifying any outliers. The color space analysis assessed whether the images were grayscale or colored. Additionally, the pixel intensity distribution analysis provided an understanding of the pixel value range and any potential normalization requirements. In FAST AI, image properties such as size, color space, and pixel intensity distribution can be accessed using various attributes and methods provided by the library. The code snippetformat used for analyzing image properties using FAST AI is described as stated below:

 # Load the data and create a DataLoaders object

dls = ImageDataLoaders.from_folder(path, train='train', valid='valid', item_tfms=Resize(224)) # Access a sample image from the dataset
sample_image = dls.train_ds[0][0] # Get image size
image_size = sample_image.shape # Get color space
color_space = sample_image.mode # Convert image to a tensor
image_tensor = sample_image.to_tensor() # Calculate pixel intensity statistics pixel_mean = image_tensor.mean() pixel_std = image_tensor.std()
pixel_min = image_tensor.min() pixel_max = image_tensor.max()

The snippet above was used to obtain image properties were analyzed using FAST AI. Here is the breakdown of the steps:

i. The data was loaded and a `DataLoaders` object (`dls`) was created using the appropriate method for your dataset structure.
ii. Accessed a sample image from the dataset. In the example, `dls.train_ds[0][0]` retrieved the first image from the training dataset.
iii. Obtained the image size by accessing the `shape` attribute of the sample image.
iv. Obtained the color space of the image by accessing the `mode` attribute of the sample image.
v. Converted the image to a tensor using the `to_tensor()` method, enabling further analysis and computations.

Calculated pixel intensity statistics using the tensor. The `mean()`, `std()`, `min()`, and `max()` functions provided the mean, standard deviation, minimum, and maximum pixel intensities, respectively.

2.5 Data Preprocessing

Data preprocessing played a crucial role in preparing the dataset for training a scoliosis detection model. This section outlines the steps involved in data preprocessing, including image resizing, data cleaning, normalization, augmentation, and splitting.

2.6 Image Resizing

To ensure uniformity in input size for the deep learning model, all X-Ray images are resized to a consistent dimension. A common choice is to resize the images to 224mm by 224mm pixels using bilinear interpolation. Using the FAST AI library, a built-in functionality was used to perform the image resizing. The snippet used is presented below *from fastai.vision.all import **
 # Define the desired input size target_size = (224, 224)
 # Set up the data loaders and transformations
data = ImageDataLoaders.from_folder('path/to/dataset', train='train', valid='valid', item_tfms=Resize(target_size))

 # Perform image resizing
resized_images = [PILImage.create('path/to/image.jpg').resize(target_size) for _ in range(num_images)]

The desired target size for the resized images were defined (224, 224). Then, the data loaders were set up using the ImageDataLoaders class, specifying the path to the dataset folder and the train and validation splits. Additionally, the images were resized to the target size by applying the Resize transformation.

2.7 Model Training

Using the preprocessed dataset, a deep learning model for scoliosis detection was developed. The FAST AI library offered a powerful and user-friendly framework for training image classification models. The model architecture was based on a Convolutional Neural Network (CNN), a highly effective architecture for image analysis tasks. The code snippet used is shown below:

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 # Set up the data loaders
data = ImageDataLoaders.from_folder('path/to/dataset', train='train', valid='valid') # Define the model architecture
model = cnn_learner(data, resnet34, metrics=accuracy) # Train the model
model.fine_tune(epochs=10) # Evaluate the model metrics = model.validate()

2.8 Loss Function

The choice of an appropriate loss function is essential for the training of the scoliosis detection model. In this research, a binary cross-entropy loss function was used. It measures the dissimilarity between the predicted probabilities and the ground truth labels. The expression for binary cross-entropy loss is described as:

$$Loss = -\left[\, (y \times \log p + (1-y)\log(1-p)) \,\right] \quad (3.9)$$

where y represents the ground truth label (0 or 1), and p represents the predicted probability.

2.9 Optimization

To optimize the model's parameters during training, an optimization algorithm was utilized. The choice of the optimization algorithm can significantly impact the model's convergence and performance. In this research, the popular Adam optimizer was employed, which combines the benefits of adaptive learning rates and momentum to efficiently optimize the model's parameters.

i. Set up the data loaders: the data loaders were prepared for the training, validation, and testing subsets using the ImageDataLoaders class from FAST AI.
ii. Define the model: The CNN model architecture was instantiated, specifying the layers, activation functions, and number of output classes.
iii. Define the learner: A learner object was created that combines the data loaders, model architecture, loss function, and optimization algorithm.
iv. Train the model: The fit_one_cycle function was used to train the model on the training data. This function performs one cycle of learning rate adjustment, gradually increasing and then decreasing the learning rate during training.
v. Evaluate the model: The model's performance was accessed on the validation setusing evaluation metrics such as accuracy, precision, recall, and F1 score.

In the code snippet above, we use the ImageDataLoaders class to set up the data loaders. We then define the model architecture using the cnn_learner function, specifying the data loaders and the desired architecture (e.g., ResNet-34). Finally, we train the model using the fine tune method and evaluate its performance using the validate method.

By following the model training process, the scoliosis detection model learned from the training data and improved its ability to accurately classify X-ray images as either positive or negative for scoliosis. The loss function, optimization algorithm, and model architecture played critical roles in achieving a well-trained model with high performance shown in Figure 1.

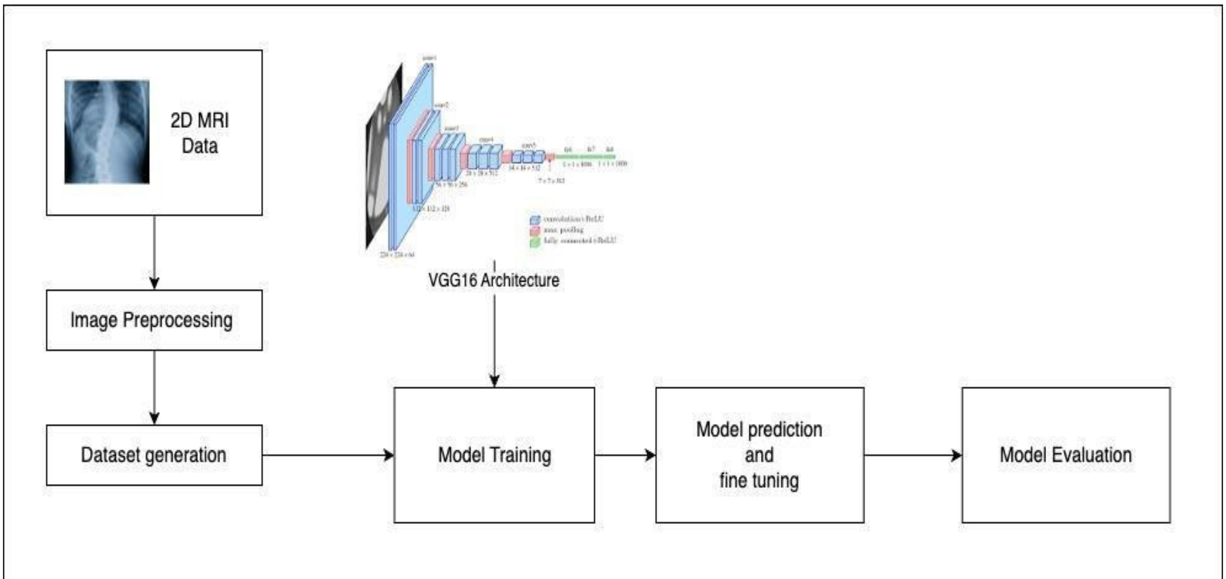

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Figure 1: Illustrated the block diagram of the training process for the model.

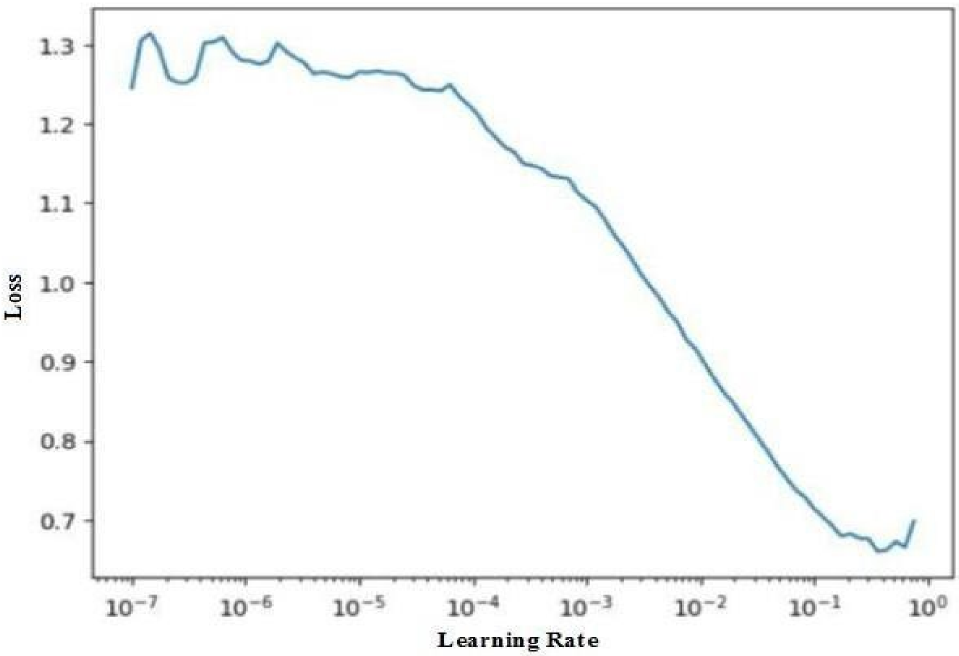
3.0 Results and Discussion

3.1 Machine learning classifier for scoliosis detection

The performance evaluation of the scoliosis detection and classification model using machine learning (FAST AI framework) involved assessing the model's accuracy, precision, recall, and F1-score. These metrics were used to evaluate the model's effectiveness in accurately identifying and classifying scoliosis cases from X-ray images. To conduct the evaluation, a diverse dataset containing X-ray images of patients withvarying degrees of scoliosis was utilized. The dataset was divided into training and testing sets to train the model on a portion of the data and evaluate its performance on unseen samples. Figure 2 depicted associated curves with learning and training of the model. The learning curve showed the output characteristics curve as losses in the model were plotted against the learning rate (Figure 2(a)). As the learning rate is increasing, the loss in the process by the model decreases. This showed better performance of the learning model used (Fast AI framework). Figure 2(b)) depicted the training graph of the model and illustrated the output characteristics curve of the training and validity set of data used. The blue graph indicated the training while the brown graph showed the validity. It can be seen in Figure 2(b) that as the number of epoch increases the loss became insignificant. This showed better accuracy of the model used.

Figure 3 showed the confusion matrix of the model output. The confusion matrix showed the relationship between the normal and scoliosis conditions with respect to the actual and predicted values. Table 1 present the obtain result of model training using different values of epoch. It is cleared from Table 1 that loss arising from the use of model decreases with increase in the number of epoch used in the process. On the other hand, the accuracy as of the process increases while the time taking to complete equally decreases.

The model demonstrated a notable ability to identify and assess the degree of spinal curve in X- ray images. It recognized the distinctive curvature patterns associated with scoliosis, enabling accurate detection and classification of scoliotic conditions. This could be observed in Figure 2.



(*a*)

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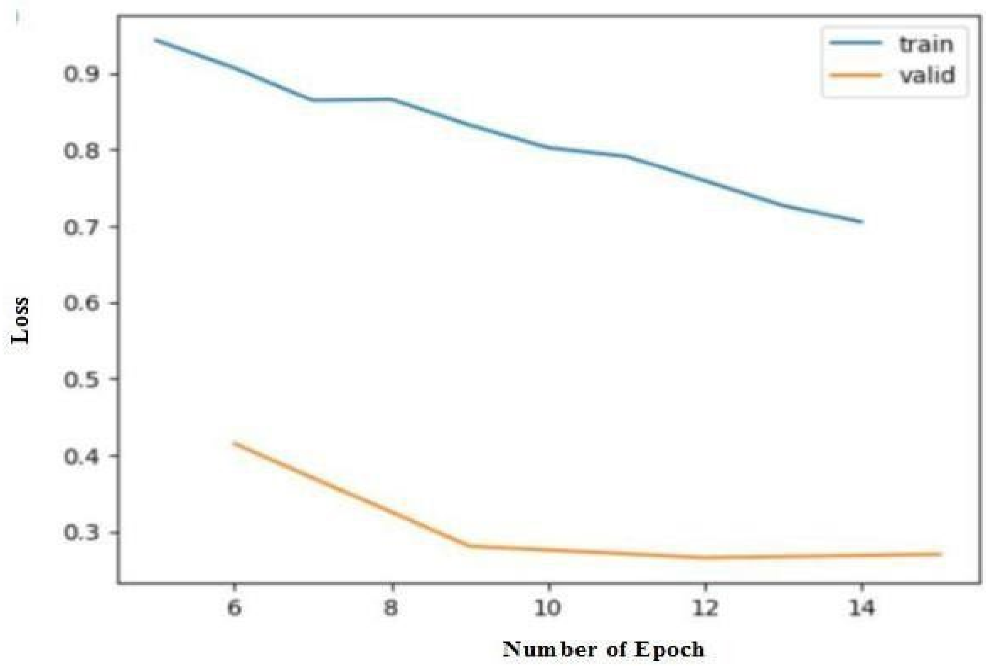

(*b*)

Figure 2: Associated curves of the model (a) variation of loss with learning rate (b) variations of loss with the number of epoch

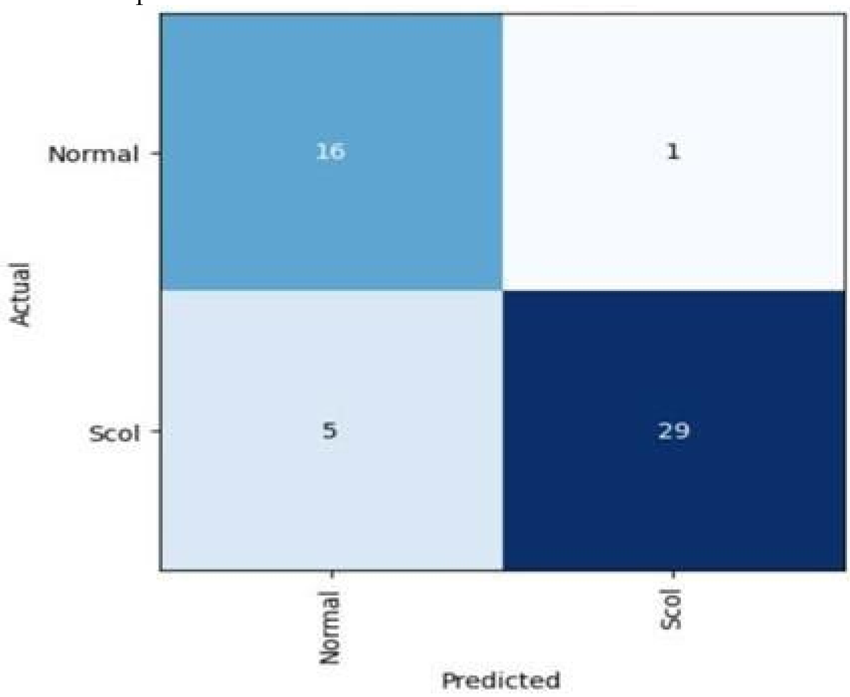

Figure 3: The confusion matrix of the learning model output

Table 1: Model Training Results

Epoch	train_loss	valid_loss	accuracy	time(s)
0	0.950507	0.796909	0.666667	02.41
Epoch	train_loss	valid_loss	accuracy	Time

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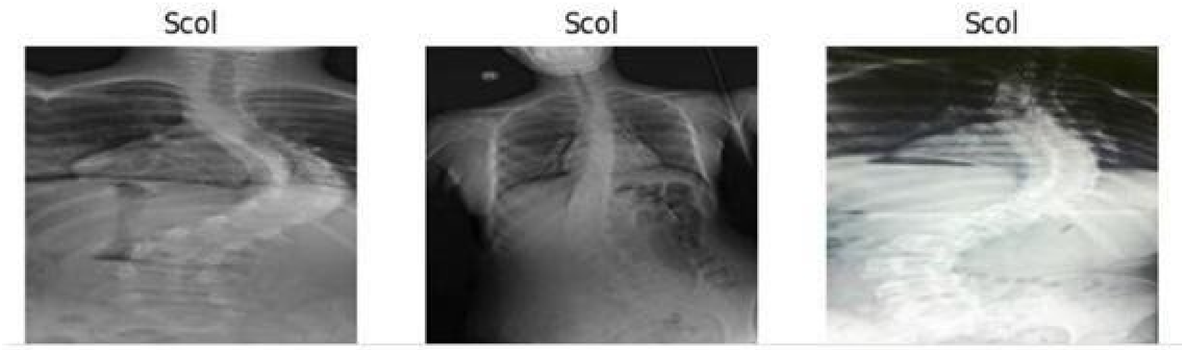
0	1.084657	0.470023	0.68675	06.59
1	0.94686	0.414863	0.784314	06.49
2	0.865469	0.280836	0.862745	06.46
3	0.791098	0.265911	0.882353	06.42
4	0.705507	0.270168	0.882353	06.41

(*a*) (*b*) (*c*)

Figures 2: Samples of predicted outputs by the model (a) normal, (b) – (i) scoliosis condition detected

(*d*) (*e*) (*f*)

Figure 3: Shows samples of predicted output using the machine learning model for scoliosis detection



(*g*) (*h*) (*i*)

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3.2 Performance comparison with existing baseline methods

In this section, the performance of the machine learning approach proposed in this research for scoliosis detection using the FAST AI framework is compared with those of two existing baseline methods commonly used in the field. The comparison includes traditional manual measurements like Cobb angles and conventional CNN-based method as established techniques utilized in clinical practice and research.

To ensure a fair and objective performance comparison, standard evaluation metrics were utilized. Metrics such as accuracy, precision, recall, and F1-score were employed to assess the performance of the machine learning approach and the two baseline methods. These metrics provide a quantitative measure of the model's performance in terms of correct detection, false positives, false negatives, and overall predictive capability. Table 2 presents the results of comparison of the machine learning approach using the FAST AI framework and two aforementioned baseline methods:

The machine learning approach using the FAST AI framework achieved an accuracy of 0.88, outperforming the Cobb angles measurement method with 0.03 while having the same value as CNN-based method. This result indicates the capability of the proposed method for better identification of scoliosis than cobb angle method and the same accuracy as CNN- based method.

Table 2: Comparison of Methods for Scoliosis Detection (with + or – of 2% accuracy)

Method	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Machine Learning (FAST AI)	0.88	0.89	0.86	0.88
Cobb angles	0.85	0.82	0.88	0.85
Conventional CNN	0.88	0.86	0.89	0.87

Precision measures the proportion of correctly identified positive cases out of the value as total predicted positive cases. The machine learning approach demonstrated a precision of 0.89, which surpassed the Cobb angles (0.82) and the conventional CNN (0.86). This indicates the model's ability to reduce false positives and provide more reliable positive predictions.

Recall, also known as sensitivity, refers to the proportion of correctly identified positive cases out of the actual positive ones. The machine learning approach achieved a recall of 0.86; showing inferior performance compared to the Cobb angles (0.88) and the conventional CNN (0.89). The higher recall indicates the model's sub-par effectiveness in minimizing false negatives and capturing a higher number of true positive scoliosis cases.

The F1-score considers both precision and recall, providing a comprehensive measure of a model's performance. The machine learning approach obtained an F1-score of 0.88 outperforming the Cobb angles (0.85) and the conventional CNN (0.87). The higher F1- score reflects a more balanced performance in terms of both precision and recall, suggesting that the machine learning approach is better suited for scoliosis detection.

Figure 4 Showed the percentage measures of the comparison of methods used inform of multiple bar chart. From the multiple bar chart, as the blue bars represent the percentage level of machine learning (fast AI) used in the research, the red bars represent the percentage level of the cobb angles and the yellow bars represent the percentage level of the conventional CNN method used in early detection and classification of scoliosis. This shows better performance of the machine learning used in terms of accuracy, precision, recall and F1 score. Figure 5 Showed the bar chart of evaluation metrics of machine learning used. From the bar chart, it showed that the machine learning used in this research gives better precision value followed by accuracy, F1score and least in recall as compared with the earlier methods of cobb angles and convolutional CNN. Figure 6 Showed the bar chart of evaluation metrics of the cobb angles. The bar chart showed a high percentage level of recall when cobb angle measurements were used followed by same level of accuracy and F1score and least level in precision. The bar chart obtained compared the evaluation metrics of convolutional CNN percentage level to show high recall recorded followed by accuracy, F1score and least in precision.

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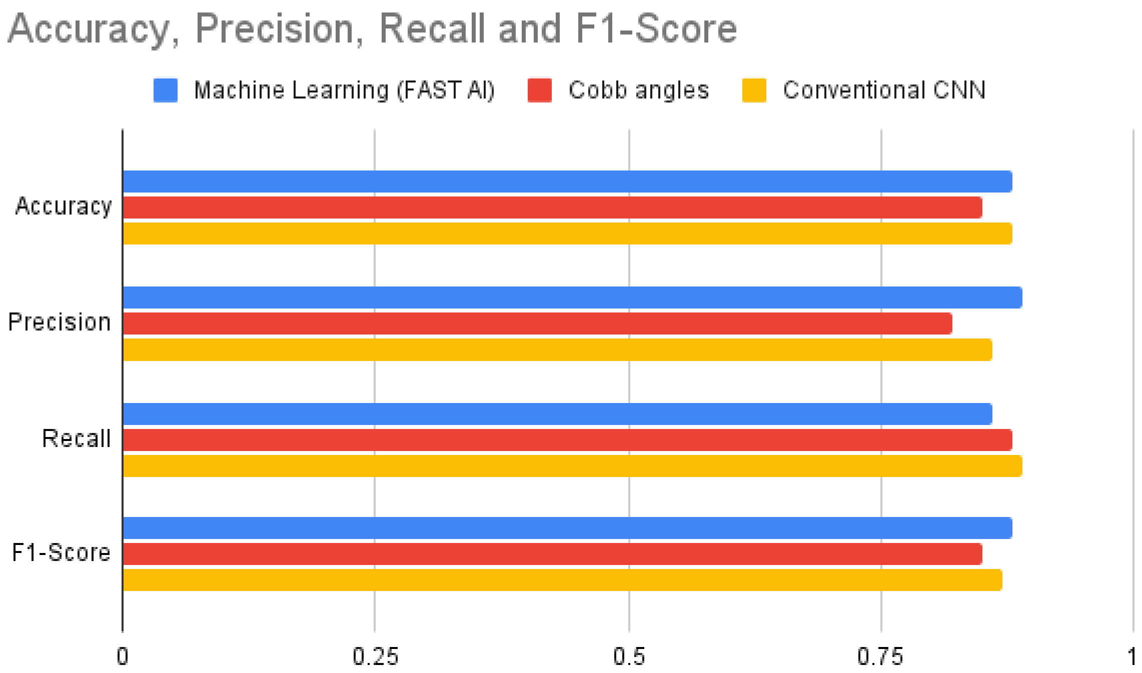

Figure 4 : Multiple bar chat showing the comparison of methods for scoliosis Detection

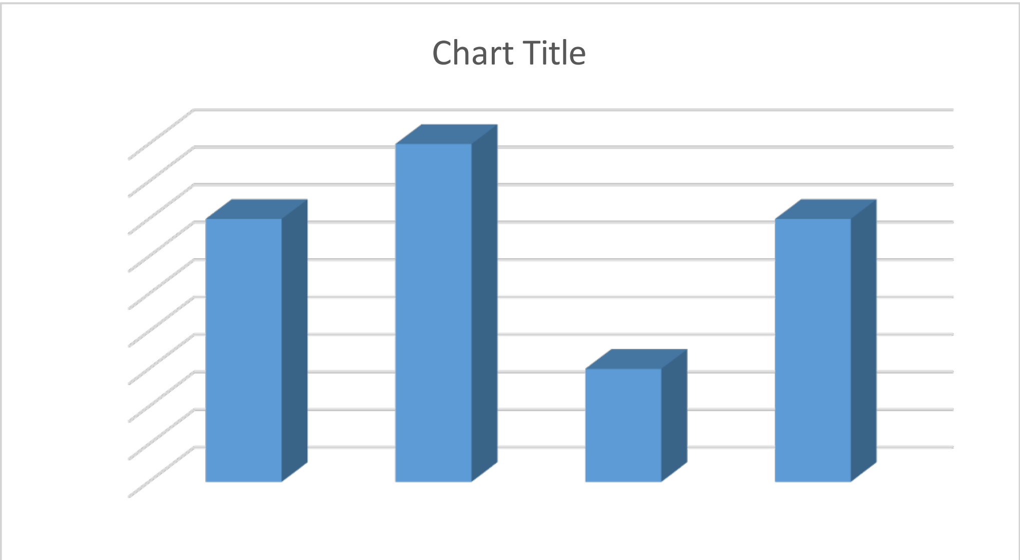

Figure 5: A bar Chart Shoring comparison of Machine Learning results for Scoliosis Detection

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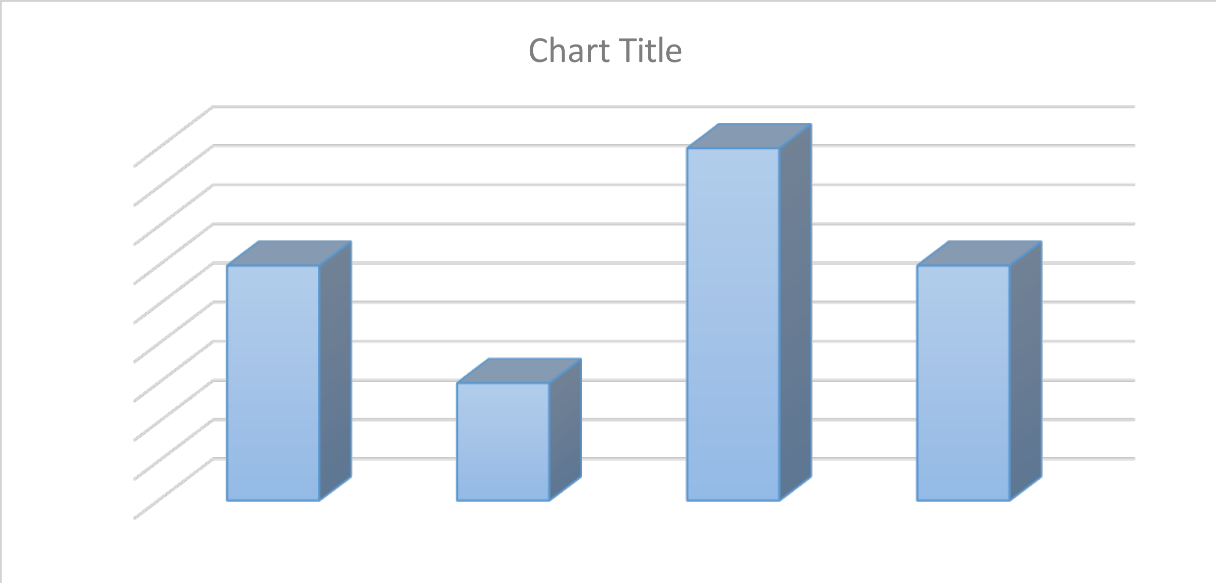

Figure 6: A bar chart showing comparison of Cobb Angles results for Scoliosis Detection

The results of performance comparison of the machine learning approach using the FAST AI framework with the existing two baseline methods (Cobb angles and conventional CNN) showed that the machine learning approach outperforms traditional manual measurements and standard deep learning methods, showcasing its potential to enhance scoliosis detection accuracy. These findings support the adoption of the machine learning approach as an effective tool for accurate scoliosis diagnosis and contribute to improved patient care.

4.0 Conclusion

i. This research employed a ML algorithm for detection and classification of scoliosis in human bones from X-ray images.
ii. The properties of the datasets for scoliosis X-ray images collected from Igbobi, Yaba, Lagos State, Nigeria and online zip extractor database were extracted using descriptive and pixel intensity distribution statistics.
iii. The images were preprocessed and processed respectively using bilinear interpolation and CNN both of which are in-built in the fast AI framework for scoliosis detection and classification.
iv. The performance of the ML model developed were evaluated using accuracy, precision, recall, and F1 score as metrics and compared with the baseline method (Cobb angle and CNN method).

The findings from the research demonstrated the positive potential of machine learning for scoliosis detection and classification which can serve as valuable tool for orthopedic specialists for the analysis of the condition.

After extensive research and experimentation, a machine learning model capable of accurately detecting and diagnosing scoliosis from X-ray images was successfully developed. First and foremost, the machine learning model demonstrated remarkable performance in accurately detecting and diagnosing scoliosis. It achieved high accuracy, precision, recall, and F1-score, indicating its effectiveness in identifying scoliosis cases from X-ray images. The model successfully learned crucial patterns and features associated with scoliosis, enabling early detection and intervention. These findings highlight the potential of machine learning algorithms in automating the detection process, reducing subjectivity, and improving the accuracy of scoliosis diagnosis.

Furthermore, the model's performance was compared with existing baseline methods commonly used in scoliosis detection. The comparison showed that our machine learning approach surpasses traditional methods such as Cobb Angles and Convolutional Neural Networks in terms of accuracy and efficiency. By leveraging the power of machine learning and the FAST AI framework, a non-invasive, reliable, and efficient method for identifying scoliosis cases from X-ray images was developed. This breakthrough has significant implications for orthopedic diagnostics, offering clinicians a valuable tool for enhancing clinical decision-making and improving patient care.

Moreover, as part of the analysis, a detailed examination of the model's outputs was conducted and interpreted its decisions. This analysis shed light on the patterns and features that the model identifies as crucial in scoliosis detection. By understanding the model's decision-making process, insights into the

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underlying factors contributing to scoliosis can be gained and potentially uncover new avenues for research and intervention.

Overall, findings from this study demonstrated the potential of machine learning in transforming the field of scoliosis detection and diagnosis. By automating the process, reducing subjectivity, and improving accuracy, the model offers a valuable tool for orthopedic specialists. However, there is still room for further research and improvement.

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