Project Report On

SpineX - Automated Spinal Disease Detection

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

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April 2025

CERTIFICATE

This is to certify that the project report entitled ***"SpineX - Automated Spinal Disease Detection"*** *is a bonafide record of the work done by* ***Neha Davis (U2103153)****,* ***Neha Mariam Mathew (U2103154)****,* ***Priya Anto (U2103167)*** *and* ***Shreya Sunil (U2103197)*** *submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in "Computer Science and Engineering" during the academic year 2021–2025.*

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ACKNOWLEDGEMENT

We wish to express our sincere gratitude towards **Rev. Dr. Jaison Paul Mulerikkal CMI**, Principal of RSET, and **Dr. Preetha KG**, Head of the Department of "Computer Science and Engineering" for providing us with the opportunity to undertake our project, "SpineX - Automated Spinal Disease Detection".

We are highly indebted to our project coordinator, **Ms. Sangeetha Jamal**, Assistant Professor, Department of Computer Science and Engineering, for her valuable support.

It is indeed our pleasure and a moment of satisfaction for us to express our sincere gratitude to our project guide **Ms. Meenu Mathew**, Assistant Professor, Department of Computer Science and Engineering, for her patience and all the priceless advice and wisdom she has shared with us.

Last but not the least, we would like to express our sincere gratitude towards all other teachers and friends for their continuous support and constructive ideas.

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Abstract

Through advanced deep learning, the SpineX project aims to radically increase the diagnostic capability by automating the detection and classification of spinal deformities as well as provide analysis on spinal conditions such as scoliosis, kyphosis, and lordosis. Traditional diagnostics depend on the manual analysis of X-ray images done by a radiologist. This approach has many subjective, time-agnostic, and inconsistent factors. SpineX works towards addressing these problems by way of a sharp input mechanism for imaging that helps provide accurate, believable, and speedy diagnosis.

The general process is basically data gathering and preprocessing, image verification as quality assurance, and deep learning models to segment spinal X-ray images for the automated detection of scoliosis. The Cobb Angle is measured, as it denotes scoliosis with regard to the curvature severity and types of curvatures. Detection and classification are made for lordosis and kyphosis using pictures taken of persons in an upright part matter, side posture. Those images are fed to specific types of neural network-based classifiers for analysis. A treatment recommendation module gives personalized recommendations such as physical therapy, posture correction exercises, and surgical evaluation.

Working with some of the state-of-the-art machine-learning architectures makes the diagnosis with SpineX precise as well as systematic. Data augmentation and preprocessing, in addition, improve model performance. Further, SpineX has a simple user interface that should ensure its integration into hospital workflows, diagnostic effectiveness, and patient outcome. It bears the potential of being game-changing for the spinal healthcare system, reducing time for diagnosis and subjective evaluation.

Contents

List of Abbreviations

- **CNN** - Convolutional Neural Network
- **MRI** - Magnetic Resonance Imaging
- **LDH** - Lumbar Disc Herniation
- **MICCAI** - Medical Image Computing and Computer-Assisted Intervention
- **ResNet** - Residual Network
- **CUDA** - Compute Unified Device Architecture (NVIDIA technology for GPUs)
- **VinDr** - Vietnam's Imaging Diagnostic Research project

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Chapter 1

Introduction

Scoliosis, kyphosis, and lordosis are commonly occurring spinal conditions; thus, to avert probable future health repercussions, quicker diagnosis and accurate identification are indispensable. It is necessary to talk about the SpineX project, which is the subject of this chapter, a system with certain features that would allow for the automated detection, analysis, and classification of spinal conditions and diseases using deep learning techniques. This project offers a better, more reliable, and accurate way of diagnosing spinal deformities while drawing comparisons with the hindrances of traditional diagnostic methods based on subjective estimates by the radiologists.

1.1 Background

Immobility, lasting pain, and declining the quality of life can be caused by the neglected disc issues. Diagnosing spinal disorders is a more cumbersome, subjective, and inconsistent practice where X-ray examinations are performed on the patient. The application of deep learning and machine learning technologies in medical imaging gives a definite solution to these issues. U-Net and convolutional neural network models are used by SpineX system to identify and categorize spinal irregularities in an automated manner. These advancements in image processing and analysis techniques facilitate more precise and dependable diagnoses, which results in enhanced efficiency and outcomes for patients. Automating procedures is the central aim of SpineX, as they seek to transform the spinal health system by modifying how various tasks are conducted, particularly in terms of patient diagnosis therefore resulting in better patient outcomes.

1.2 Problem Definition

The SpineX project is expected to create an automatic system which can detect, classify and analyze spinal deformities such as scoliosis, kyphosis and lordosis. It will utilize Deep Learning to calculate the Cobb angle for scoliosis and analyze side posture images for lordosis and kyphosis. Besides classification, the system will provide personalized treatment recommendations - physical therapy, posture correction exercises or surgical evaluation - defined by the severity and type of the deformity. Overall to increase diagnostic efficiency, reduce subjective evaluations and improve patient outcomes through timely and accurate assessments.

1.3 Scope and Motivation

Scope: The project is intended to detect spinal disorders paying extra attention to hyper-kyphosis, hyper-lordosis, and scoliosis. This will involve problems in background segmentation for some X-ray views of the spine curvature measurement (Cobb angle for scoliosis), deformity classification, and treatment recommendations based on the severity of the condition. The system employs some very sophisticated deep learning techniques and assures accuracy, consistency, and timeliness of the diagnosis, and even the preventive measures by accommodating physical therapy, corrective exercises, and surgical evaluation when necessary.

Motivation: There are significant opportunities to improve the treatment outcomes through early and accurate diagnosis of spinal abnormalities in children and adolescents. Manual diagnostic techniques available till now are unreliable, subjective to judgment, slow, and tedious. The project therefore aims to develop such an automated system, which will address the problems by making them available to the masses while alleviating work pressure on radiologists and improving accuracy in spinal curvature measurement.

1.4 Objectives

- Compile a database that consists of x-ray images and posture pictures and then utilize image processing to improve the quality of the pictures.
- Build a convolutional neural network, CNN model to verify the legitimacy of the

supplied x-ray images if it is considered a spinal x-ray.

- For scoliosis detection in x-ray images apply self-supervised learning to extract and segment the spinal area through u net.
- To determine the degree of scoliosis carry out x ray imaging and divide these images in between normal and scoliosis and then compute the Cobb angle.
- To distinguish between spinal deformities like kyphosis and lordosis put specialized neural network classifiers using postural images including side posture images.
- Put a spinal deformity with the type of kyphosis, kyphosis, lordosis or scoliosis alongside its severity and recommend treatment options such as postural correcting exercises, physical therapy and surgical evaluation.

1.5 Challenges

SpineX has a series of daunting problems. One of them is to make sure that the quality of the X-ray images is uniform as the deviations can have a bearing on the performance of the model. Another challenge is to identify and isolate the spinal column in each X-ray for proper examination. Such clinical intervention as measuring the spinal curvature angle, for example, the Cobb angle used for scoliosis, is also a large problem as it is for assessment of the degree of the condition and making good choices of requisite treatment modalities. Finally, the evaluation and the classification of lordosis and kyphosis from side posture photographs add one more activity to the algorithm.

1.6 Assumptions

- The spinal region X-Rays are basically used for spotting scoliosis and for the precise measurement of Cobb angle.
- Side way photos of humans are used as a source for finding and classifying kyphosis and lordosis.
- The performance and generalizability of these models can be improved through augmentation of data.

1.7 Societal / Industrial Relevance

Because it can significantly alter how clinicians make diagnoses in orthopedic and radiology departments, this initiative bears considerable societal as well as industrial significance. It increases consistency of the diagnostic process and minimizes dependence on subjective manual analysis through an automated, accurate, and efficient method of diagnosis. Because the mechanism is open and cheap, isolated areas and communities with limited healthcare infrastructure would stand to benefit tremendously, thus facilitating access to spinal care. It integrates easily into hospital operations as key industrial value, thereby allowing clinicians to improve patient outcomes.

1.8 Organization of the Report

The report is divided into several chapters that guide the reader through different aspects of the project. Chapter 1 introduces the background, problem definition, scope, motivation, objectives, challenges, assumptions, and the societal and industrial relevance of the work.

Chapter 2 of the report reviews the key research papers, summarizing findings and identifying gaps in existing literature, which serves as the foundation for the project.

Chapter 3 discusses the system design architecture and component design, use case diagram, tools and technologies, dataset used in the application module breakdown, key deliverables and project timeline.

Chapters are progressing in a cumulative manner from one chapter to another, that is, from a problem identification basis, to design and implementation.

1.9 Conclusion

This project report deals with the growing challenges in diagnostics and analyses related to spinal deformities like scoliosis, kyphosis, and lordosis. High-level automation will be used for detecting, classifying, and measuring different spinal abnormalities from X-ray and side images. This project intends to achieve accuracy along with efficiency and reliability in diagnosis. Deep learning models will be included so that personalized treatment recommendations can be offered. This project will contribute toward healthcare technology advancement improvement outcome delivery and support to the medical community in timely and effective intervention for patients suffering from some spinal deformities.

Chapter 2

Literature Survey

2.1 Spinal deformity detection from X-Rays

Analyzing changes in the spine through X-rays is perhaps one of the most relevant diagnosis methods for scoliosis, kyphosis, lordosis, and other structural disorders. This has been one of the very phenomenal developments in deep learning-modern automated systems in being able to detect and classify defects with really high accuracy-Of course, with the intent that radiologists will be assisted in faster and perhaps more reliant readings of how the spine aligns and abnormalities.

Indeed, these X-ray films are some of the good things to diagnose the spinal deformity concerning scoliosis and kyphosis. Recently, however, there was developed by deep learning automated detection systems with impressively high classification performance apart from the dimension of defects viewed. The most important thing here is that these systems, powered by artificial intelligence, assist radiologists in speeding up their evaluations and offering a more accurate assessment of the subject's spinal alignments and abnormalities as viewed through X-ray images.

2.1.1 VinDr-SpineXR: A Deep Learning Framework for Spinal Lesions Detection and Classification from Radiographs by Nguyen et al. (2021) [1]

VinDr-SpineXR is essentially a deep learning framework developed for detecting and determining spinal lesions in X-ray images. Under the VinDr project is a large set of skeletal X-ray images annotated to help the radiologists with diagnosis. The method is basically based on convolutional neural networks(CNNs) for detection of vertebral fractures, degenerative changes, and other spin disorders. It provides very good performance on lesion detection and classification provided by diversity of CNN architectures along with better data augmenting and pre-processing methods. This shows that there is much more potential in improving the clinical management of spinal X-ray through accurate automated review.

Classification Network

The network takes as input X-ray images of the spine to determine the probability that the examined scan is abnormal. The weights were optimally tuned against cross-entropy loss for three ensemble CNN architectures: DenseNet-121, DenseNet-169, and DenseNet-201, which were trained on normal and abnormal spines. The final decision concerning the classification task is taken using an optimal threshold defined by Youden's index: the power of classifying an X-ray as abnormal is predominantly based on its specificity and sensitivity.

Detection Network

The system uses a two stage detector, the first is Fast R-CNN, which makes initial suggestions, while the other is Sparse R-CNN, which uses the attention mechanism to perform enhancement in iterations. They have been used in the identification of seven categories of spine lesions: osteophytes, disc space narrowing, vertebral collapse, among others.

Each detector was trained on region-level classification and bounding box regression in order to detect anomalies and boost detection capabilities with augmentation methods. Faster R-CNN has given rise to initial suggestions, whereas Sparse R-CNN has enhanced the suggestions in repetition or iteration and has detected seven different spine lesions: osteophytes, disc space narrowing, vertebral collapse, and others.

Decision Fusion and Performance Optimization

To fuse the outputs of the classification and detection networks in maximizing the accuracy of lesion detection, a fusion rule is applied as follows:

If the probability of an image being abnormal goes beyond a threshold (c*), retain all the lesion detection results. If that probability comes below c*, then only those bounding boxes with an overall above 0.5 confidence value are retained, to reduce false positives for low confidence cases.

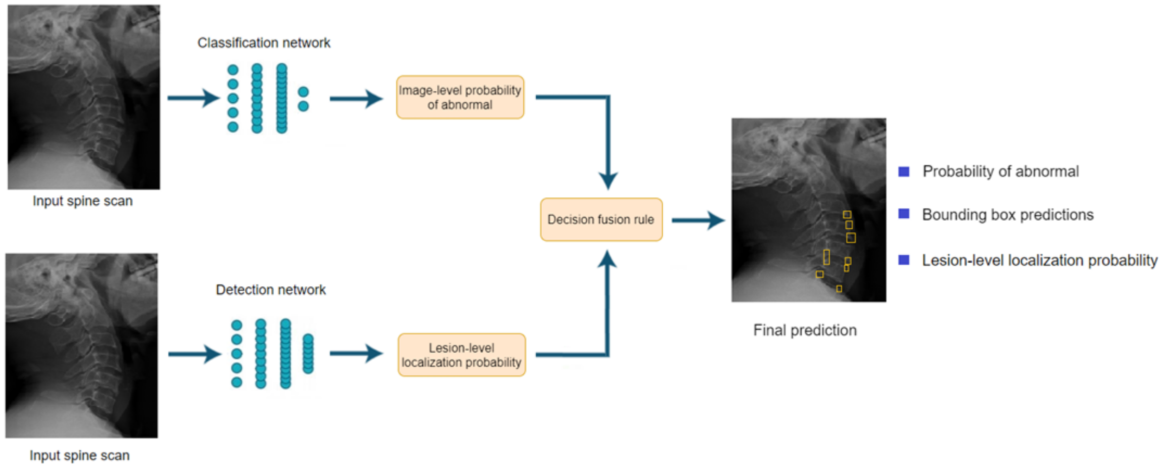


Figure 2.1: VinDr-SpineXR Framework for Spine Anomaly Detection

2.1.2 A Dual Coordinate System Vertebra Landmark Detection Network with Sparse-to-Dense Vertebral Line Interpolation by Zhang and Chung (2024) [2]

S2D-VLI VLDet is a state of the art vertebra landmark finding network built for scoliosis assessment. This technique is further upgraded by a dual-coordinate auxiliary estimator and a sparse-to-dense interpolation scheme through design in order to accurately suit spine X-ray applications. An encoding-decoding architecture makes the network extract and decode the important features, which are finally used in landmark localization. The precision with which the system is created makes it perfect for vertebra landmark detection and hence improves scoliosis assessment and planning treatment. [2].

Vertebra Landmark Detector Framework and Dual Coordinate System

Several key vertebrae landmarks are identified with the aid of spine X-ray images by the S2D-VLI VLDet conception, which is the center and corner point coordinates that play an integral role in Cobb angle calculation. The first stage consists of extracting essential features from the image through modified ResNet34 backbone, which is configured with five convolutional blocks for denoting between E1 to E5. They are extracted as follows: E1-E2 for simple structure features, E3-E4 for bendable shape moderate features, and E5 makes the "condensed high-level details" compact. The decoder thus has three convolutional blocks (D1 to D3) for the vertebra landmark predictions encoded from the modified feature maps.

There are six custom passages through which the decoder decodes: heatmap pathway for the center locations within the vertebrae, center offset pathway for refining center point positions, corner boundaries are estimated using this corner offset pathway employing polar coordinates, intervertebral spacing measure in CPIE and AVIE, and last but not least vertebral line interpolation pathway which models the curvature of the spine. All different loss functions like heatmap loss and offset regression losses are utilized in optimizing landmark detection. Focal loss makes the network robust, especially in low-contrast areas in X-rays. robustness, particularly in low-contrast regions of X-rays.

By combining both Cartesian coordinates-the center point localization-with polar coordinates for the corner localization, the dual-coordinate system provides an advantage for localization in spatial aspects through linear and rotational measurement. This enables an accurate landmark localization, even in the case of irregularly shaped vertebrae. It also enhances the reliability in Cobb angle measurements through the coordination of Cartesian and polar coordinates, thus adapting the network to the various configurations of the spine.

Presents the dual-coordinate system: The coordinates allow combination, that is: for center point localization, they are indicated in Cartesian; for corner localization, in polar; thus, linear and rotational spatial aspects. This will enable precise landmark localization, even for irregularly shaped vertebrae. The combination of polar and Cartesian coordinates will thus result in an enhanced reliability for the Cobb angle measurements and in adaption of the network to the various configurations of the spine.

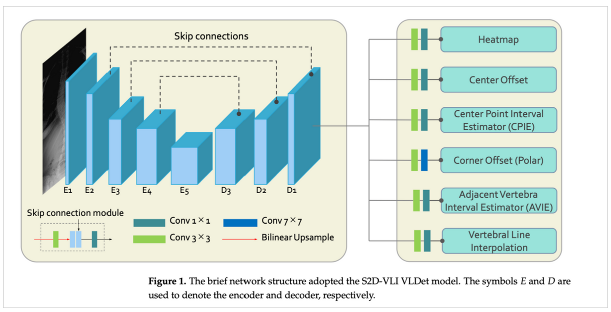


Figure 2.2: S2D-VLI VLDet network structure

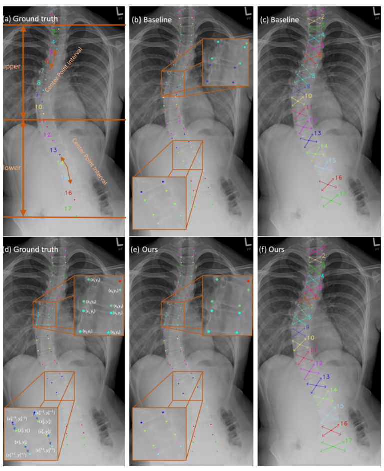


Figure 2.3: S2D-VLI VLDet model results

Center Point Interval Estimator (CPIE) and Adjacent Vertebra Interval Estimator (AVIE)

CPIE is the Center Point Interval Estimator and AVIE is the Adjacent Vertebra Interval Estimator. They will enhance the methods used for the detection of vertebral landmarks. In particular, CPIE will calculate anticipated distances between vertebral centers; that is, it will define intervals within which the whole spine will be in its natural alignment, especially for difficult X-ray areas. AVIE enhances landmark predictions using the spatial relationships between adjacent vertebrae, thereby improving detection in interferences, such as dense tissues. Both estimators give more outputs for some extra supervision signals internalizing the network by localization of landmarks vertebrae across different sets of given anatomical regions. Other main techniques may include Inter-Vertebral Line Interpolation, which densifies sparse training labels towards teaching the network smooth spinal patterns and accurate curvature profiles. The measurement of Cobb angles and the diagnosis of scoliosis can very much benefit from this method because it draws a smooth continuous line straight through the centers of the vertebrae. This method would enable the continuous and reliable detection of spinal landmarks applicable in clinical assessment and treatment of scoliosis in complex spinal alignments and low-quality X-rays.

2.1.3 Automatic segmentation of lumbar spine MRI images based on improved attention U-net by Wang et al. (2022) [3]

Lumbar spine disorders, like disc hernias and scoliosis, increasingly plague people within most age ranges. Since all of these problems depend on rapid, accurate diagnostic interpretation, segmentation of lumbar spine MRI automation would be significant for the reducing the burden for radiologists as well as efficient diagnosis.

Attention Mechanism in Lumbar Spine MRI Segmentation

Lumbar spine MRI segmentation is a very essential part of diagnosing spinal disorders like herniated discs, scoliosis, and spondylolisthesis. But the challenge manifests in that noise and anatomical variation are present, along with a number of artifacts that quite significantly interfere with accurate segmentation. Traditional CNNs are unable to solve such a complex situation. Attention U-Net is proposed to address the contribution toward enhancing the given situation, by introducing an attention mechanism into the model that allows the model to concentrate on the important parts of the image. This really helps to better highlight the essential anatomical structures like vertebrae and intervertebral discs which in turn enhances the accuracy of segmentation and leads to better and more reliable results.

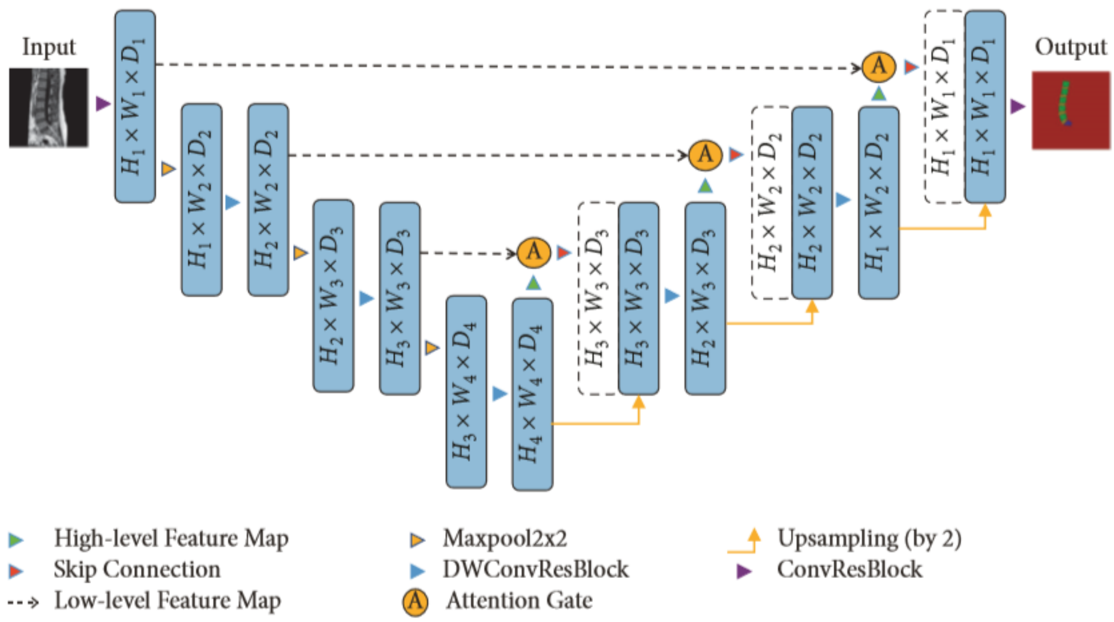
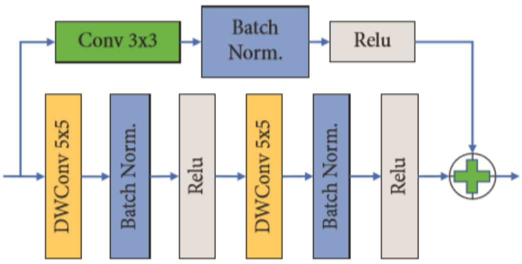


Figure 2.4: The network structure of Improved Attention U-Net.

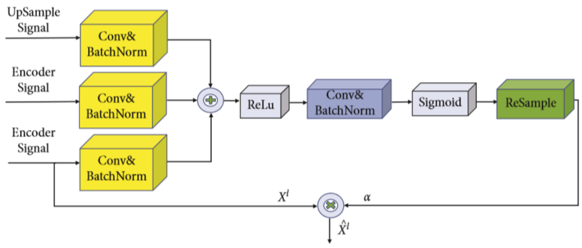
Improved Attention and Residual Modules

The residual modules and attention mechanism are improved to enhance the performance of the Attention U-Net model. On one hand, the residual learning serves to resolve the vanishing gradient problem, using skip connections to preserve key features, improve feature propagation especially in medical images with high variability, and enable deeper representation learning of lumbar spine structures, even if such representations exist amidst noise.

The improved attention module assigns varying weights for focusing attention on critical anatomical regions of lumbar spine MRI scans and thus reduces the effects of irrelevant areas. The approach improves segmentation accuracy and robustness, especially in challenging scenarios, by emphasizing the most relevant features for better overall performance.



(a) Improved residual blocks.



(b) Improved attention module.

Figure 2.5: Improved residual and attention modules.

Experiment and Clinical Impact

We used a total of 420 T1-weighted MRI images of lumbar spine obtained from 180 patients for the experiment. Adaptive histogram equalization was applied to improve contrast and ease the differentiation between features such as intervertebral discs and vertebrae. The images were then annotated into categories such as vertebral bodies, discs, and the sacrum, and prepared for deep learning-based segmentation. The improved Attention U-Net model was able to do the segmentation with subsequent post-processing to get better, clearer extraction of the spine structures.

In comparison with other models like SVM, FCN, R-CNN, U-Net, and even the original Attention U-Net, this model results proved to be far better in accuracy, recall, and especially the Dice coefficient. Clinically speaking, this shows promising abilities in identifying spinal conditions such as herniated discs and scoliosis. This might help reduce the workload on radiologists while increasing accuracy at hand. This model finds its value in routine and more intricate cases of spinal care.

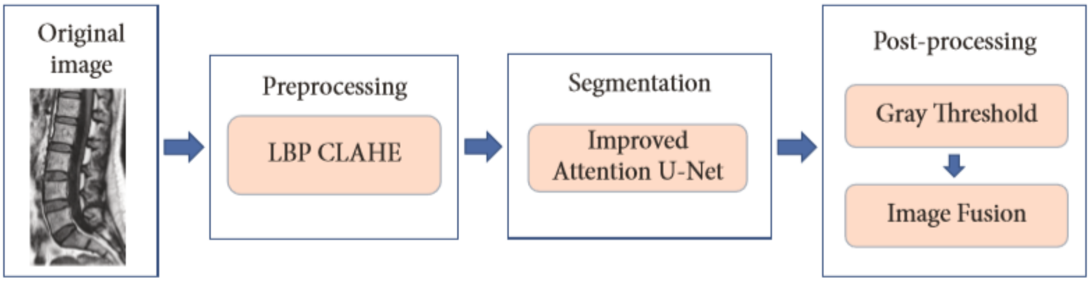


Figure 2.6: Segmentation process of lumbar spine image.

2.1.4 Deep learning-based detection and classification of lumbar disc herniation on magnetic resonance images by Zhang et al. (2023) [4]

The development of deep learning models for automated detection and classification of lumbar disc herniation (LDH) on axial T2-weighted MR images is based on Faster R-CNN region detection followed by classification on ResNeXt101 models. The model is intended to enhance diagnostic efficiency and accuracy, using 15,249 images labeled by radiology experts from 1,115 patients. Evaluation metrics such as Intersection Over Union (IoU), accuracy, precision, and AUC yielded an internal IoU of 0.82 and an external IoU of 0.70, with 87.7% accuracy and AUC of 0.965, demonstrating highly aligned outcomes with expert grades.

Detection Using Faster R-CNN

Faster R-CNN algorithm combines region proposal generation and detection, making it ideal for detecting the lumbar disc herniated region. Key steps involve image preprocessing via ResNet-50, region proposal generation, ROI pooling, classification, and detection.

- Resizing the image to 320x320 pixels and normalizing data into the range of [0, 1].
- Feature extraction by ResNet-50 through hierarchical flow, which overcomes the vanishing gradient issue.

- The Region Proposal Network (RPN) generates bounding boxes for potential LDH regions from anchor boxes, calculating initial objectness scores and subsequently refining the bounding boxes.
- The ROI pooling layer assigns fixed-size feature maps to the proposed regions to reduce computational complexity.
- The Fully Connected layer performs classification and bounding box regression on the flattened features.
- Non-Maximum Suppression (NMS) cleans up confidence predictions of bounding boxes and removes duplicates.

Classification Network using ResNeXt101

MSU Severity Grades

The MSU classification system grades lumbar disc herniation as follows:

- **Grade 0**: No herniation.
- **Grade 1**: Herniation extends less than 50%.
- **Grade 2**: Herniation extends more than 50%.
- **Grade 3**: Herniation extends beyond the intra-facet line.

The architecture of ResNeXt101

The architecture of ResNeXt101 consists of several stages, each comprising multiple **ResNeXt blocks**. These blocks consist of a series of convolutions that process the input feature maps in a parallel manner. The flow of the network is outlined below:

- **Initial Layer**: 7x7 Conv, Max Pool.
- **Stage 1**: 3 ResNeXt blocks (1x1, 3x3, 1x1).
- **Stage 2**: 4 ResNeXt blocks.
- **Stage 3**: 23 ResNeXt blocks.

- **Stage 4**: 3 ResNeXt blocks.
- **Final Layer**: Global Average Pooling + Fully Connected Layer.

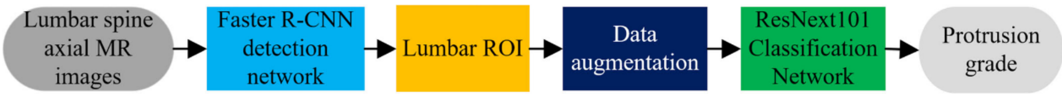


Figure 2.7: Lumbar Disc Herniation Detection and Classification Flowchart.

2.2 Summary and Gaps Identified

Deep learning has shown considerable promise in spinal image analysis, potentially improving both diagnostic accuracy and clinical efficiency. Recent research focuses on automating tasks such as lesion detection, vertebral landmark localization, segmentation, and lumbar disc herniation classification. While these advances are significant, problems remain, and further progress is needed to make these models even more successful and helpful. This section addresses notable studies and areas that warrant additional research.

2.2.1 Gaps Identified

Deep learning has improved the interpretation of spinal images by automating processes including as segmentation, landmark localization, and lesion diagnosis. Improving these models' efficacy and dependability in actual clinical situations is still difficult, though. This section identifies important research gaps and topics that require more work to improve the application of deep learning in spinal healthcare.

1. **Data Diversity and Generalization:** A lot of models rely on particular datasets that could not accurately reflect the wide range of variability observed in actual clinical settings, such as variations in patient demographics, imaging technology, and picture quality. This makes it more difficult for models to be applied to a variety of populations.

2. **Interpretability and Explainability:** Although deep learning algorithms can be extremely accurate, the black box nature of them often prevents practitioners from understanding the decision-making process that is essential to building trust and acceptance in the medical sphere.

3. **Manage Noisy and Low-data Quality:** Although some attempts have been made in overcoming this challenge, there remain great difficulties in operational models while using noisy, low-resolution, and less complete data as found in any biomedical clinical environment. More robust techniques are thereby required for results to be conspicuously efficient in such areas.

4. **Cross-Modal Model Robustness:** Most models were either designed for a single imaging modality (X-ray, MRI) or, at the very least, will have expected performance views with more alternate imaging types. The allied modeling effort would prove to validate the utility of imaging data being of different types.

5. **Real-time Performance and Scalability:** Even while deep-learning models had shown almost good accuracy, they could not quite assure clinical expectations for real-time performance: that decisions must be triggered within clinically necessary real-time constraints. It remains a puzzle within itself to optimize these models for speed of inference and deployment to big settings.

While recent deep learning developments for spinal image processing have showed a lot of promise, there are still a number of obstacles to be addressed. To make sure these technologies are dependable, scalable, and extensively used in clinical practice, it will be essential to address problems like data diversity, model interpretability, robustness to noisy data, cross-modal capabilities, and real-time performance. To effectively utilize AI's promise in spinal health diagnostics, future research should concentrate on enhancing these areas.

2.2.2 Summary

The table summarizes four studies using deep learning for spinal image analysis, including VinDr-SpineXR for lesion detection, Dual Coordinate System for landmark localization, Improved Attention U-Net for MRI segmentation, and classification of lumbar disc herniation. AI can improve accuracy and speed in healthcare workflows, diagnostic support, and spinal disease evaluation. AI technologies have made great progress in improving spinal health diagnosis through everyday medical practice.

Name of the Author(s)	Advantages	Disadvantages
Nguyen et al. (2021)	High accuracy in lesion localization and classification in spinal X-rays.	Requires a large, annotated dataset for training, which may not always be available.
Zhang and Chung (2024)	Improved precision and robustness in vertebra landmark localization.	The complex architecture may demand high computational resources.
Wang et al. (2022)	Enhanced segmentation performance in complex or noisy MRI images.	Needs a large amount of annotated data for effective model training.
Zhang et al. (2023)	High accuracy in detecting and classifying lumbar disc herniation.	Performance can vary depending on the quality and diversity of MRI data used for training.

Table 2.1: Summary of Studies on Spinal Imaging and Lesion Detection

Chapter 3

Requirements

3.1 Hardware Requirements

- **Processor:** Intel Core i7 processor (or comparable AMD processor) that has a minimum of 4 cores, and a base clock speed of 3.0 GHz or higher. A high-performance processor can yield faster calculations when training the model, and when processing images.

- **Graphics Processing Unit (GPU):** NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1080, RTX 2070, etc.) with a minimum of 6GB of VRAM or higher. A powerful graphs processor will speed up deep learning calculations and make model training faster.

- **RAM:** Minimum of 16GB RAM (32GB recommended for faster processing). More RAM will allow for better handling of high-resolution images and complex neural networks without experiencing sluggishness.

- **Storage:** SSD with minimum storage space of 512GB for datasets and models. Using an SSD will allow for faster read/write times for loading large medical imaging datasets and neural network checkpoints.

- **Operating System:** Windows 10/11 or a Linux-based operating system (e.g., Ubuntu 18.04 or higher) in order to be compatible with deep learning frameworks, and GPU acceleration support.

- **Display:** Full HD or better resolution display for increased visualization of images and results. A larger and higher quality display will help with visualizing X-ray images with the correct segmentation outputs.

3.2 Software Requirements

- **Operating System:** Windows 10/11 or Linux (the recommended version is Ubuntu 18.04) as these operating systems will provide adequate software support to install and run machine learning libraries and install the GPU driver.

- **Deep Learning Frameworks:**
  - TensorFlow 2.x – Deep learning framework that is designed with tools for training and deploying neural networks. It also provides a Keras API for those interested in higher level use without sacrificing lower-level flexibility.
  - Keras 2.x – Easy to use neural network library that relies on TensorFlow. Keras is designed to greatly simplify the process of building, training and fine-tuning deep learning models.
  - PyTorch 1.x – Flexible deep learning framework that has become the go-to framework for research applications. Pytorch allows you to create dynamic computation graphs and include debugging features.

- **Image Processing Libraries:**
  - OpenCV 4.x – Open-source powerful library for computer vision that can help with image processing applications such as filtering, edge detection and image segmentation.
  - scikit-image 0.18+ – Python based library that has a toolbox of algorithms for image processing. Algorithms include feature extraction, contrast enhancement and noise reduction.

- **Other Libraries:**
  - NumPy 1.x – foundational Python Library for scientific computing that specializes in array manipulations. NumPy serves as the building block for many data science libraries.
  - Pandas 1.x – Plotting and visualization library supporting plots and graphs allowing some tracking of model performance, as well as representation of medical image statistics.

  - Matplotlib 3.x – Visualization library used to generate plots and graphs, helping in analyzing model performance and illustrating medical image statistics.
  - Seaborn 0.11+ – Enhanced data visualization library for making various types of statistical plots to facilitate exploration of data distribution and patterns that is built on Matplotlib.

- **Cloud-based Environment:** Google Colab (for training models, especially with GPUs for accelerating performance). Google colab can be leveraged for high-performance cloud GPUs for typical analytics use cases and deep learning, without the investment in local heavy computational resources.

- **Version Control:** Git (for version control and collaboration). Git can keep track of changes in a codebase, but it also supports collaboration on coding projects, and integrates seamlessly with development platforms such as GitHub for project management.

Chapter 4

System Design

This chapter gives an overview of the basic design and development framework of the SpineX project. An introduction of the system architecture is given with a more elaborate explanation of the design and action of its major components, all directed toward achieving the expected outputs. The chapter goes in-depth on those architectures, techniques, and assumptions of the data flow, all considered indispensable for carrying out the functions needed to fulfill the goals of the current proposal.

To represent the systematic approach adopted, the chapter discusses critical aspects such as the tools and technologies employed, the rationale behind the choice of datasets, and the methodology for splitting the project into manageable modules. The chapter describes in detail the key deliverables, the finalized schedule for the project, and the work breakdown structure that provided the strategic orientations for the conduct of the work throughout the project period.

The chapter also elaborates upon integration of these elements to provide one seamless framework for thorough and efficient execution. In conjunction with other components, these aspects lay a solid foundation for SpineX's vision of turning spinal healthcare on its head and improving outcomes for patients.

4.1 System Architecture

The architectural diagram of SpineX provides a complete picture of its components, interactions, and the workflow in general- how the data flows within the system, and how different modules work together in such a way that it reaches accurate and efficient detection of spinal deformities. The architecture of the system is illustrated below:

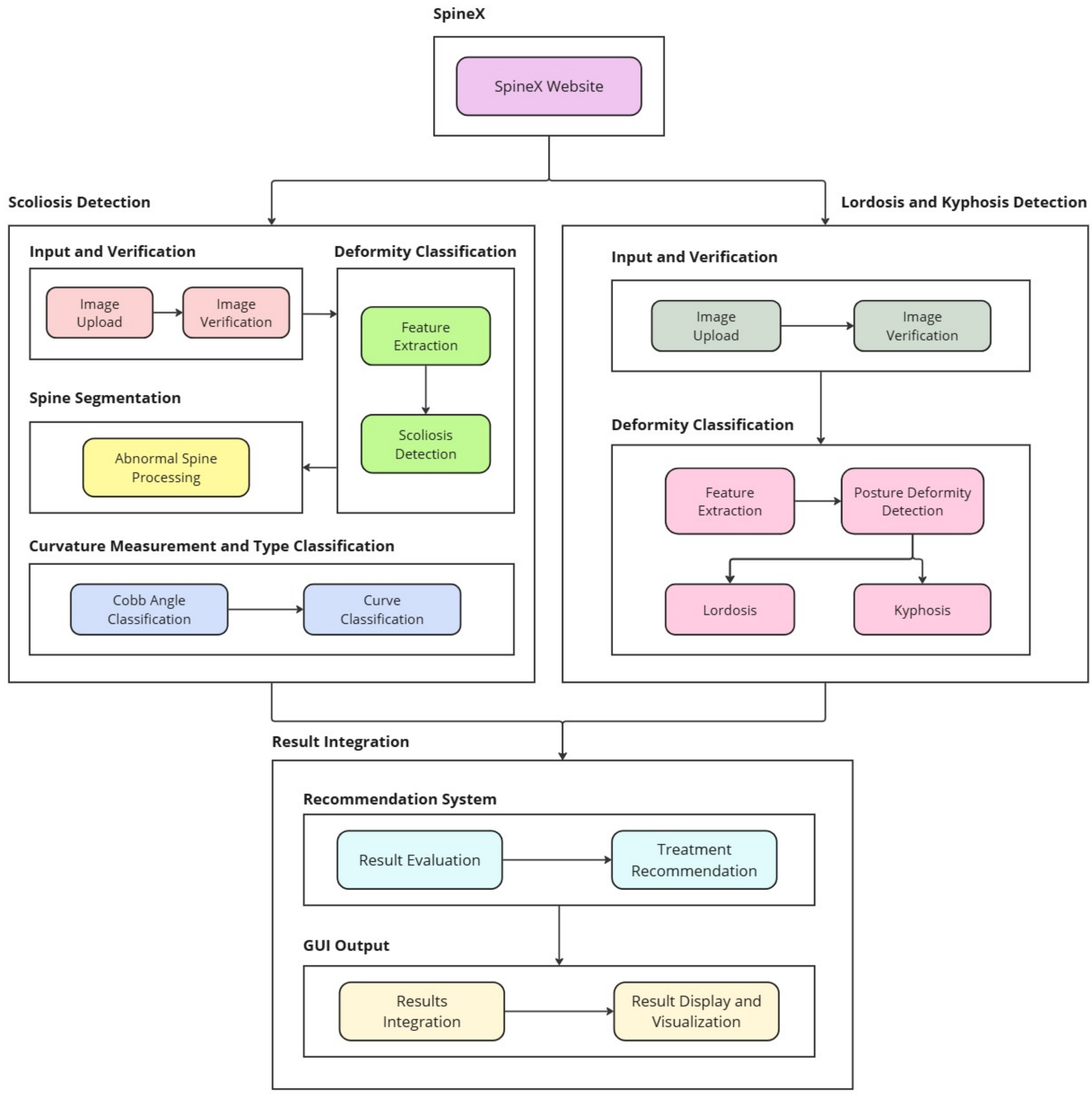


Figure 4.1: Architecture Diagram

Various modules are present in the SpineX architecture to detect diseases like scoliosis, lordosis and kyphosis, and to use a merged recommendation system. This helps in assisting in diagnostic process making it effective and well-detailed. The main elements are:

1. **Scoliosis Identification:** This module helps in recognizing and examining scoliosis abnormalities.This includes the following phases:
   - Input and Validation: This includes uploading and verifying the image to ensure correct data entry.
   - Deformity Classification: This retrieves features from the images and implements scoliosis classification.
   - Spine Segmentation: Analyzes irregular spine structures for subsequent exam ination.
   - Curvature Assessment and Type Categorization: Computes the Cobb angle and categorizes the curve type for improved diagnosis.
2. **Lordosis and Kyphosis Detection:** This module handles the detection of lordosis and kyphosis deformities. It includes:
   - Input and Verification: Allows for image upload and verification.
   - Posture Deformity Detection: Combines feature extraction with posture deformity detection to classify abnormalities into:
     - Lordosis: Detects excessive inward curvature of the spine.
     - Kyphosis: Identifies excessive outward curvature of the spine.
3. **Recommendation System** The recommendation engine takes in the outputs of both scoliosis and lordosis/kyphosis detection modules and merges them into
   - Result Evaluation: Evaluate the abnormalities detected.
   - Treatment Recommendation: Recommend possible treatment options based on the results.
4. **Web Interface** The web graphic interface allows for ease of results display.

- **Technology Stack:** Implemented with a React frontend and a Flask backend.
- **Results Integration:** Combines and displays all outputs from all functional modules.
- **Visualization:** Provides simple and interactive results tied to possible diagnoses and results treatment of spinal deformities; is intuitive for both a patient and practitioner.

In modular architecture, one gets clear-even interactive demo presentation to users without compromising to assure delivery of and proper prescriptions for suitable treatments for any of the associated spine deformities to the spinex system. Its architecture, therefore, turns a bit too complicated, though surprisingly quite very good for application on both the side of the patients and also by the doctors; hence very supportive in creating efficient and smooth results.

4.2 Component Design

4.2.1 Scoliosis Detection Module

The method for the identification of scoliosis utilized a Convolutional Neural Frame (CNN) that was developed for the analysis/classification of X-ray images of the spine. Each image was uploaded and resized to 224 px by 224 px and normalized for consistent input. The CNN architecture consisted of three convolutional and max-pooling layers to reduce spatial dimensions while preserving relevant features. After acquiring the relevant features, a flattening layer was utilized before a connected fully connected (dense) layer. The dense layer was next connected to a softmax activation function that enabled multi-class categorization of identified spinal deformities. The model was validated via accuracy and loss metrics on the validation dataset, and visually demonstrated performance through application of confusion matrices, and accuracy/loss plotting to determine training behavior.

Transfer learning is utilized to facilitate improved accuracy and generalization in the model, with the backbone being the pre-trained InceptionV3 architecture. The pretrained InceptionV3 was pretrained on the ImageNet dataset, with the top classification layers removed and replaced with custom layers for binary scoliosis classification. The base layers of the InceptionV3 network are frozen, in order to maintain the learned features; further, a Global Average Pooling layer, a Dense layer utilizing ReLU activation, and a Dropout layer were added to mitigate overfitting. The final classification layer has a single neuron and a Sigmoid activation function to yield binary output. The model utilized Adam optimization (learning rate 0.001) and binary cross-entropy as its loss function, with accuracy tracked during training. In order to increase reliability, Early Stopping and Model Checkpoint callbacks are used to halt model training when validation loss plateaus and to save the best model weights, respectively, in order to ensure the best detection performance.

4.2.2 Spine Segmentation Module

The Spine Segmentation component is an essential part of the scoliosis detection pipeline because it segments the spine from the rest of the X-ray image for further assessment. The design does not use a deep learning segmentation network (e.g. U-Nets) and utilizes classical image processing methods to effectively segment the spinal region that is lightweight and interpretable. The steps for spine segmentation are described in the bullets below:

- **Contrast Enhancement (CLAHE):** The grayscale X-ray image is pre-processed using Contrast Limited Adaptive Histogram Equalization (CLAHE) for improving local contrast. Enhancing contrast improves the imaging of the spinal structures, especially those regions that are inherently low contrast.

- **Focused Central Region Masking:**A vertical mask is applied to limit consideration to only the central portion where the spine is positioned in an X-ray image. Masking the central region reduces background noise and limits the area of focus to a likely area for the spine to be in.

- **Thresholding and Morphological Processing:** A simple intensity thresholding operation is then used to extract bright spinal structures. Morphological operations, specifically closing and then opening, are used to connect fragmented vertebrae through dilation and remove small artifacts through erosion.

- **Vertical Continuity Enforcement:** Gaps in the segmented spine region are filled to maintain continuity along the vertical axis by checking for vertical pixel consistency within a defined window.

- **Dilation and Component Filtering:** The processed binary mask is dilated along the vertical direction in order to capture the entire extent of the spine. Connected component analysis is applied to retain only those components with sufficient vertical height, thus removing smaller regions that do not correspond to the spine.

- **Final Spine Isolation and Overlay:** The final refined mask of the spine is overlaid onto the original Enhanced x-ray image for visualization. The final result displays only the region of the spine, which can be used for classification and information on curvature.

This image-processing based approach can be a faster and more robust method of detecting the spine for image processing tasks than using neural networks, especially in instances where computational resources are limited or interpretability is important.

4.2.3 Keypoint Generation and Curvature Measurement

Keypoint Generation and Curvature Measurement module can identify fundamental anatomical landmarks along the spine and provides a measurement of severity in terms of Cobb angle. It facilitates the ability to develop keypoints automatically or manually, for flexibility and accuracy.

- **Automated Keypoint Generation:** The segmented spine is momentarily skeletonized to a 1-pixel-wide centerline. Is fitted with a smoothing-spline (UnivariateSpline) to fit the spinal curve, and 50 evenly spaced points are sampled from the fit. From the sampled points, five keypoints are automatically derived based on maximum lateral deviation and transitions in the curve, in the form of an upper peak, a transition, and a lower peak.

- **Manual Keypoint Generation:** The user can manually identify five anatomical landmarks by clicking on the image. The five points will include two points along the upper and lower curves, these can include the transition point, which is duplicated internally for the you calculate two Cobb angles for the upper and lower curves.

- **Cobb Angle Measurement:** Cobb angle is an measurement of spinal curvature which quantifies the angle between two lines drawn along the tilted vertebrae on the apex and inflection of the curve. The system calculates two angles based on the keypoints selected and will report the largest angle of the two Cobb angles as final Cobb angle, which will be used to determine scoliosis severity.

4.2.4 Lordosis and Kyphosis Detection Module

The Lordosis and Kyphosis Detection Module detects lordosis and kyphosis spinal deformities based on side posture images. . The main activities of this module are outlined below:

- **Input and Validation of Images:** The component considers images taken while the patient is in the side posture and evaluates them for quality and correctness. This should ensure that the images meet the necessary standards for detecting deformities.

- **Feature Extraction and Posture Deformity Detection:** Deep learning techniques are used to extract relevant features from lateral views of posture images. The system will learn features of lordosis and kyphosis based on the direction of curvature and the magnitude of the deformity.

- **Lordosis Detection:** In this situation, the spine curves outwards and the curvature's severity is measured to categorize the image as portraying lordosis.

- **Kyphosis Detection:** It is generally linked with direction in which the spinal curvature extends outwards along the curvature and measures the severity or degree of kyphosis using the curvature.

4.2.5 Recommendation System

The results of the modules are evaluated by the recommendation system therefore helping in detection of diseases like scoliosis,lordosis, and kyphosis and then suggests personalized treatment recommendations. Based on the type of disease and the deformities found, the recommendation system provides treatment suggestions for the individuals with spinal deformities. The modules include the following:

- **Evaluation of Results:** The evaluation of results of deformities like scoliosis, lordosis, and kyphosis detection, provide an understanding about the severity of the deformity and helps in determining the appropriate level of treatment based on the results in this module.
- **Recommendations for Treatment:** The treatment and the corresponding recommendations may vary based on the type of the deformity detected. It might range from simple treatment measures like physical therapy which are used for early or moderate deformities to extreme corrective measures for comparitively simple types.
- **Posture Correction:** Mild deformities may warrant the recommendations of exercises to minimize the effects of curvature in the spine. Specifically, exercises dealing with postural correction and relief were taught here.
- **Evaluation for Surgery:** In case of severe scoliosis, lordosis, or kyphosis, the SpineX system helps recommend whether surgical procedures are required to treat the deformity. If the severity of deformity is high, surgery would be recommended.

4.3 Use Case Diagram

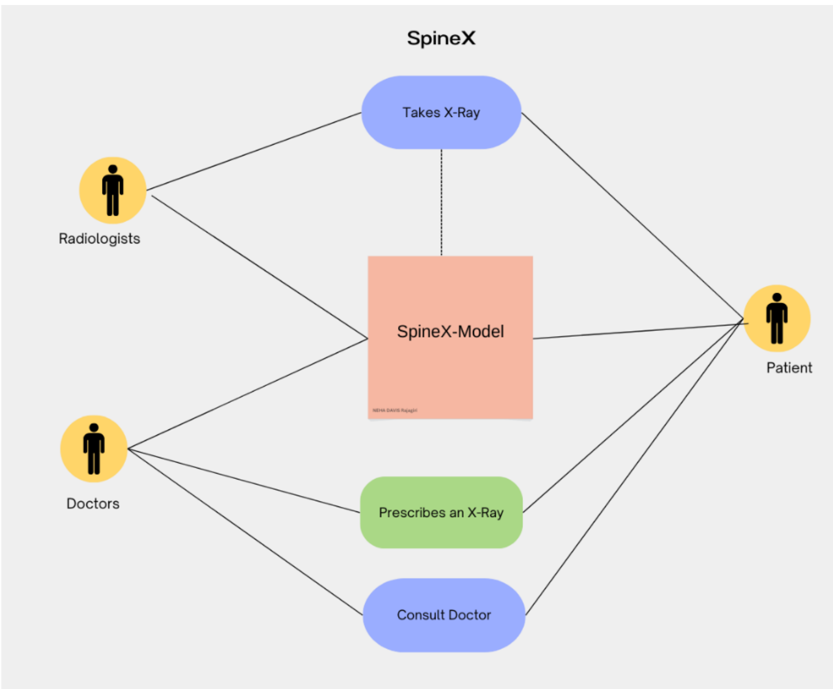


Figure 4.2: Use Case Diagram.

4.4 Tools and Technologies

4.4.1 Hardware Requirements

1. High-Performance CPU: Intel Core i7 or its equivalent is an example of a multicore processor that could facilitate the smooth working of computer intensive tasks such as image preprocessing which is followed by image segmentation and then proceeding with classification. The CPU can also efficiently perform runtime tasks which include feature extraction and data augmentation.

2. Dedicated GPU with CUDA Support: For deep learning purposes an Nvidia RTX series or other comparable device is highly encouraged since it would lessen the time taken to train convolutional neural networks and also facilitate the real time segmentation and image classification tasks. Using a GPU to assist with model training greatly enhances efficiency while working with large datasets.

3. 16GB/32GB RAM: Seamless multitasking, large storage of images and performing multiple processes simultaneously all require a substantial amount of memory. Adequate Memory ensures the smooth transition and operation of the multiple steps involved in the model training pipeline, the preprocessing steps and the final step which is segmentation.

4. 64-bit Operating System: To use the useful advanced machine learning frameworks and tools one would require a 64 bit Linux or preferably windows 11 as they are modern operating systems. Additionally, the 64 bit architecture is compatible with good memory management for large datasets.

4.4.2 Software Requirements

1. Python: Python is a popular, versatile, and easy-to-use high-level programming language with an impressive library ecosystem. It's currently the most used language for programming. Since it already supports most modern features of programming and also works with most of the state-of-the-art machine learning frameworks and tools, at least version 3.9 is recommended. compatibility with the latest machine learning frameworks and tools.

2. Development Environment: Google Colab and Jupyter Notebook are used for coding, experimentation, and visualization. Google Colab allows one to use a GPU free of cost for handling the computation of complex tasks, while Jupyter Notebook provides an interactive development and debugging platform on a step-by-step basis.

3. Python Libraries: Deep learning model development, image preprocessing, handling of data, and visualization are done through libraries such as TensorFlow, Keras, OpenCV, NumPy, Pandas, Matplotlib, and scikit-learn. The mentioned libraries will form a complete toolkit necessary for the realization of key functionalities of the project.

4. Version Control Systems: Git and GitHub are used to create versions and collaborate on the same; these keep the codebase in good condition and share it amongst team members or for external reviews.

4.5 Dataset Identified

For the SpineX project, we utilized various datasets to train and evaluate the deep learning models. The main dataset used for identifying scoliosis consists of the "Vertebrae X-ray Images", which is an open-source dataset featuring images of both scoliosis and normal conditions. Furthermore, the "Posture Types Image Dataset (side view)" was utilized to detect lordosis and kyphosis conditions. This open-source dataset provides side-view images to detect spinal abnormalities. To enhance the model's accuracy, we created a custom dataset, guaranteeing a variety of high-quality samples for training. These datasets collectively assist in the thorough identification and precise classification of spinal deformities within the SpineX system.

4.6 Module Division and Work Breakdown

4.6.1 Modules Divisions

a) **Data Collection and Preparation**

This module collects enough X-rays and sideview images which after a careful examination confirms all the images are also suitable for detecting spines that are deformed. The captured data undergo pre-processing which comprises image resizing, noise, and data normalization to ensure quality data suitable for the models that are going to be trained is adequately captured.

b) **Verification and quality assurance of x-ray**

This phase makes certain that the X-ray images obtained are of satisfactory quality with regards to performing analysis X-ray images. It assesses the picture for quality in three dimensions: orientation, clarity and artifacts, evidence of each of the three contradicts the premise.

c) **Classification of spinal deformity**

In this module, the condition of the spine is either normal or has scoliosis depending on the abnormalities detected on the x-ray images. The diagnosis of deformities in the spine is further made simpler because of this classification, which is termed as binary classification.

d) **Spine Segmentation**

Here, the spine is distinguished from the surrounding parts in the x-ray images and a more precise view of the spine structures to diagnose deformities and irregularities is retained.

e) **Curvature Measurement and Curve Type Classification**

In case of scoliosis, the degree of Cobb angle would be calculated in order to determine the angle of the curvature. Furthermore, this module also classifies the angle into types of scoliosis curve, that is C or S, as well as measuring how severe it is so as to ensure appropriate treatment can be provided.

f) **Feature Extraction and Posture Deformity Detection**

This module operates in a very simple manner whereby the user takes and uploads a side view and other images of their body and this is used by the system to detect any sort of deformities in the posture being exhibited, including lordosis or kyphosis. This feature helps in determining the degree of such conditions and their severity thereby aiding in complete assessment of the spine.

g) **Treatment Guidance and User Interface**

The last module integrates the analysis results and provides recommendations related to specific treatments. Some of such treatments may be physical therapy or correcting a patients sitting posture and in more extreme cases suggest for surgery. A brief overview of the results should be made available through a simple user interface together with the practical guidance.

4.6.2 Work Breakdown

Team Member	**Module**
Neha Davis	Deformity Classification & Analysis
Neha Mariam Mathew	Data Collection & Preprocessing, GUI
Priya Anto	Model Development & Angle Measurement
Shreya Sunil	Segementation & Web Development

Table 4.1: Work Breakdown

4.7 Key Deliverables

The following key deliverables outline the main outcomes and contributions of the SpineX project:

- **Automated Spinal Deformity Detection System:** A system enabling the detection and classification of spinal deformities into subclasses: scoliosis, lordosis, and kyphosis, based on spinal and postural images, respectively.

- **Accurate Curvature Measurement:** An algorithm developed to measure the Cobb angle, allowing for accurate grading of scoliosis and degenerative spinal deformities. This has improved diagnostic accuracy by providing precise curvature measurements.

- **Treatment Recommendation Engine:** This engine provides treatment recommendations by diagnosing the types of deformities present and recommending appropriate actions, such as physical therapy, posture correction exercises, or surgical assessment, if necessary.

- **User-Friendly Interface:** A user-friendly graphical user interface would allow the user to easily upload an image and view the results afterwards, establishing a more pleasant environment for the patient as well as the doctor.

- **Comprehensive Diagnostic Reports:** Computerized reports will include types and severities of detected deformities. Such reporting would therefore give very useful information for health care providers in their decision making with regard to treatment modalities.

4.8 Project Timeline

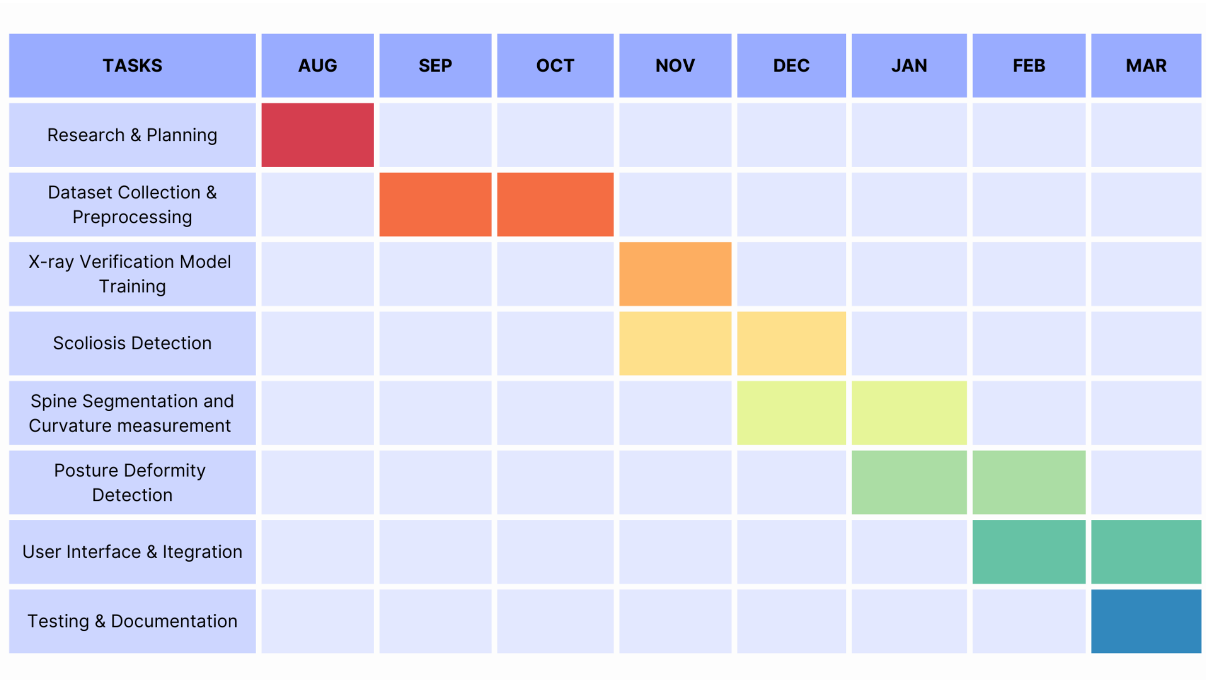


Figure 4.3: Project Timeline.

This section targets how the system architecture is done, which includes different modules besides the technology used in the development of these different modules as well as the accomplishments promised from this system.

Chapter 5

System Implementation

The SpineX system utilizes deep learning techniques to completely automate automatic detection and classification of spinal deformities using X-ray and posture images. This section describes the methods used, including dataset creation, preprocessing, an architecture based on convolutional neural networks (CNN), and transfer learning. The system employs segmentation and morphological techniques to help better extract spinal structures. Further, the system computes the Cobb angle to measure scoliosis severity and detects kyphosis and lordosis to support diagnosis and treatment recommendations.

5.1 Dataset Collection And Image Preprocessing

The SpineX system is built on two main datasets: a dataset for scoliosis and a dataset for side posture. The scoliosis dataset consists of X-ray images of the spine's vertebrae which were sourced from Kaggle datasets that are publicly available and manually collected samples to attempt to balance normal and scoliosis samples. Augmentation techniques included rotation, flipping, and zooming, which were applied using the 'ImageDataGenerator' function to achieve more variety in our datasets and improve classification measures. The Posture Types Image Dataset was accessed through Kaggle to use for identifying lordosis and kyphosis. The images within the dataset have been categorized to Lordotic, Kyphotic, and Neutral images on their side view. The background has been removed and the subject in each image has been faced in the same direction. In addition, images were added to the dataset. Complementary augmentations were applied, including rotation, shifting, shearing, zooming, and flipping horizontally to improve generalization. Each dataset underwent an 80%-10%-10% split comprising, training, validation, and testing datasets respectively. All images were resized to 224×224 pixels to maintain consistency throughout our datasets. The scoliosis dataset underwent a normalization step to limit image variability, and EfficientNet's preprocessing function was used on the side posture dataset for normalization.

5.2 CNN Model

A CNN model that uses input 224 × 224 × 3 images was developed for scoliosis detection. The model architecture consists of three convolutional layers with 32, 64, and 128 filters (3 × 3 kernel, ReLU activation) and is followed by a 2 × 2 max-pooling layer after each conv layer. After convolution and max-pooling, the output is flattened and passed through a dense layer with 128 neurons (ReLU), then to a softmax output layer. The model was trained with the Adam optimizer, a loss function of sparse categorical cross-entropy, and accuracy is the main metric. During training, backpropagation reduces loss and addresses imbalanced data with class weights. The accuracy and loss were monitored during the training for each epoch to avoid overfitting. The training history was eventually visualized by Matplotlib to understand the model performance.

```
model = models.Sequential([
    layers.Input(shape=(224, 224, 3)),
    layers.Conv2D(32, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(len(CLASS_NAMES), activation='softmax')
])


model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Figure 5.1: CNN Model.

5.3 Transfer Learning Approach

To improve the performance of scoliosis detection, the SpineX team performs transfer learning using the pre-trained InceptionV3 model as a backbone. InceptionV3 was first trained on the ImageNet dataset. To use InceptionV3 as a feature extractor for binary classification, the top classification layers were removed, and custom layers added. The base layers of InceptionV3 are frozen, to maintain the feature representations it learned from ImageNet, and only train the top custom layers. The architecture has a Global Average Pooling layer to reduce dimensionality, followed by a Dense layer with a ReLU activation to introduce non-linearity and a Dropout layer to reduce overfitting. The classification layer is a single neuron with a Sigmoid activation function for binary classification of scoliosis.

The model is compiled utilizing the Adam optimizer with a learning rate of 0.001, utilizing binary cross-entropy as the loss, and accuracy as the metric. Moreover, during training, Early Stopping and Model Checkpoint callbacks will ensure improved training and will prevent overfitting. Early Stopping will check the validation loss, and if it does not improve a given number of epochs, it will stop training while restoring the best weights achieved. Model Checkpoint will keep saving the best of the model throughout training, and thus ensuring the best performance of the model.

```
# Model definition using InceptionV3 as base model
base_model = InceptionV3(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Freeze base model layers for initial training
for layer in base_model.layers:
    layer.trainable = False

# Add custom layers for binary classification (Normal vs Scoliosis)
x = layers.GlobalAveragePooling2D()(base_model.output)
x = layers.Dense(512, activation='relu')(x)
x = layers.Dropout(0.5)(x)
output = layers.Dense(1, activation='sigmoid')(x)  # Sigmoid for binary classification

# Define and compile model
model = Model(inputs=base_model.input, outputs=output)
model.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', metrics=['accuracy'])

# Callbacks for early stopping and model checkpointing
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
model_checkpoint = ModelCheckpoint('scoliosis_model.keras', save_best_only=True)
```

Figure 5.2: Transfer Learning Model.

5.4 Cobb Angle Classification

In order to evaluate spinal deformities, especially scoliosis, SpineX uses a specialized method for calculating the Cobb angle, widely viewed as the standard measure of the degree of spinal curvature. The approach includes segmentation, keypoint extraction, angle measurement, and classification.

5.4.1 Heuristic Segmentation for Spine Extraction

Prior to measuring the Cobb angle, it's pertinent to effectively separate the spine from the X-ray images.This is done by a heuristic segmentation approach that follows several steps to increase visibility of the spine and the quality of any subsequent analysis:

- **Central Region Masking:** A vertical mask is applied to view only the spine's central region and remove unwanted anatomical noise (i.e. ribs, or organs) from the X-ray.
- **Thresholding and Morphological Processing:** Regions of high intensity that correlate to the spine's dense structures are extracted via thresholding. Morphological operations (such as dilation and closing) are applied to connect broken pieces of structure, while removing small specks of noise.
- **Ensuring Vertical Continuity:** Sometimes, due to X-ray quality or related posture, the spinal column may be depicted as an interruption. In this step, these interrupted regions are connected to ensure a vertical spine.
- **Component Filtering:** Connected component analysis are used to filter small irrelevant blobs (or structures) present in the image. Only the largest component in the image (likely the spine) is kept.
- **Final Spine Masking:** The filtered connected components are then combined to create clean and focused spine region in the X-ray for further analysis.

```
_, thresholded = cv2.threshold(central_region, 200, 255, cv2.THRESH_BINARY)


kernel = np.ones((5, 5), np.uint8)
cleaned = cv2.morphologyEx(thresholded, cv2.MORPH_CLOSE, kernel)
cleaned = cv2.morphologyEx(cleaned, cv2.MORPH_OPEN, kernel)
```

Figure 5.3: Intensity Thresholding and Morphological Operations(Opening and Closing).

5.4.2 Cobb Angle Calculation

After the spine has undergone isolation, the next step is to identify important anatomical landmarks that will allow for Cobb angle calculation.

a) **Keypoint Extraction**

The goal off this step is to identify the vertebral endplates, which are flat regions of the vertebrae representing anatomical landmarks for calculating spinal deformation. More complex systems may utilize convolutional neural network (CNN) trained to identify vertebral endplates. Five landmarks will be identified from the spinal curve. Landmarks 1, 2 and 3 will be used to define the upper curve, where Landmark 1 identifies the beginning of the curve, Landmark 2 identifies the maximum deformation along the curve, and Landmark 3 identifies the end of the upper curve, which also serves as the beginning of the spinal curves lower portion. Landmarks 4, and 5 will be used to define the lower curve, where Landmark 4 identifies the maximum deformation, and Landmark 5 identifies the end of the lower curve.

```
# Load the filtered image (for point extraction and processing)
filtered_image = cv2.imread('/content/filtered.jpeg', cv2.IMREAD_GRAYSCALE)
filtered_image = (filtered_image > 128).astype(np.uint8) * 255  # Ensure binary

# Skeletonization
skeleton = skeletonize(filtered_image > 0)
coords = np.column_stack(np.where(skeleton > 0))
coords = coords[np.argsort(coords[:, 0])]
y_vals = coords[:, 0]
x_vals = coords[:, 1]

# Fit a smooth curve
unique_y, unique_indices = np.unique(y_vals, return_index=True)
unique_x = x_vals[unique_indices]
spline = UnivariateSpline(unique_y, unique_x, k=3, s=1)

# Sample points along the curve
num_points = 50
sample_y = np.linspace(unique_y[0], unique_y[-1], num_points)
sample_x = spline(sample_y)

# Compute deviations from the centerline
mid_x = np.mean(sample_x)
deviations = np.abs(sample_x - mid_x)

# Identify 5 Key Points
half_idx = len(sample_y) // 2
point_2_idx = min(np.argmax(deviations[:half_idx]) + 2, half_idx - 1)
point_4_idx = np.argmax(deviations[half_idx:]) + half_idx
point_3_idx = (point_2_idx + point_4_idx) // 2
point_1_idx = max(0, point_2_idx + 5)
vertebrae_above = 15  # Adjust for Point 1
```

Figure 5.4: Automated Keypoint Detection.

b) **Angle Measurement**

After these points are identified, two linear regression lines are fitted. The first line fits Points 1 to 3 and represents the upper curve, while the second line fits Points 2 to 5 and represents the lower curve. These are assigned slopes m_1 and m_2, respectively, although arbitrarily defined.

The Cobb angle, represented by θ, is then calculated using the equation:

$$\theta = \tan^{-1}\left(\frac{|m_1 - m_2|}{1 + m_1 \cdot m_2}\right)$$

This equation calculates the angle between both lines that have been fitted, the result will be in radians which will then be converted to degrees to be a more clinically relevant and clear measure of spinal curvature.

```
def calculate_cobb_angle(points):
    # Get the coordinates of the three points
    x1, y1 = points[0]
    x2, y2 = points[1]
    x3, y3 = points[2]

    # Calculate the slopes of the two lines
    m1 = (y2 - y1) / (x2 - x1) if x2 != x1 else float('inf')
    m2 = (y3 - y2) / (x3 - x2) if x3 != x2 else float('inf')

    # Calculate the angle between the two lines in radians
    if m1 == float('inf') or m2 == float('inf'):
        angle_rad = np.pi / 2  # 90 degrees if one line is vertical
    else:
        angle_rad = abs(np.arctan((m2 - m1) / (1 + m1 * m2)))

    # Convert angle to degrees
    angle_deg = np.degrees(angle_rad)
    return angle_deg
```

Figure 5.5: Cobb angle measurement.

5.5 Lordosis, Kyphosis, and Neutral Classification

The CNN model, which utilizes EfficientNetB0 as a backbone, can accurately classify spinal posture into one of three categories - Kyphosis, Lordosis, and Neutral. The model benefits from using transfer learning since it relies on pre-trained weights from the ImageNet dataset, which allows for meaningful spinal curvature feature extraction. The model incorporates data augmentation techniques, which were applied (e.g. for training) including rotation, shifting, shearing, zoom, and flip. Data augmentation, which was applied for training, allows the model to generalize to the inherent variation in spinal posture while providing the model with additional robustness in performance. The classification head consists of a Global Average Pooling layer followed by a fully connected ReLU layer (128 neurons), a dropout layer (rate = 0.5), and a softmax output layer for the three-class classification problem. Training was optimized using an Adam optimizer for efficient convergence, and evaluation of performance using a confusion matrix indicated strong classification performance, with separation of classes within the three groups. Overall, the model demonstrates strong reliability and efficiency, and could be seen as an effective tool for automated assessment of spinal postural assessment in a clinical or research capacity.

```
# Load EfficientNetB0 model without the top layer
base_model = EfficientNetB0(include_top=False, weights='imagenet', input_shape=(img_height, img_width, 3))
base_model.trainable = False  # Freeze base model initially

# Add custom layers
model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(3, activation='softmax')
])

# Unfreeze last few layers of EfficientNetB0 for fine-tuning
base_model.trainable = True
fine_tune_at = 100  # Start fine-tuning from the 100th layer
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001),  # Lower learning rate for fine-tuning
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Figure 5.6: Lordosis and Kyphosis Classification Model.

5.6 Treatment Recommendations

Following a decision map based on the classification results and Cobb angle estimates, this rule-based decision system provides personalized recommendations for treatment. In terms of scoliosis, the recommendation is applied to severity: Cobb angle less than 20° would suggest physiotherapy and follow-up, Cobb angle between 20°–40° suggests bracing (e.g., Boston or Milwaukee braces) and rehabilitation, and Cobb angle greater than 40° would suggest a surgical consult (this includes surgical procedures such as spinal fusion or vertebral tethering). For lordosis and kyphosis, the classification outputs indicated what the corrective measures that would be taken. Generally, lordosis would be treated through core-strengthening exercises and postural correction with bracing being used in the most severe cases. Kyphosis with a Cobb angle less than 50° would be treated via postural training and stretching, with treatment included bracing for Cobb angle greater than 50°, and a surgical evaluation for Cobb angle greater than 70°. Thus, this automated decision-mapping system will establish an organized AI decision-making structure for the rehabilitation of spinal disorders.

5.7 Chapter Conclusion

The detection of spinal disorders using a multi-faceted approach starts at the heuristic segmentation step, whereby the spine is segmented from the X-ray images so that we can ensure the spinal curvature is in focus for subsequent analysis. Critical landmarks are then labelled so that we may calculate the Cobb angle using linear regression and trigonometric solutions, which is a paramount clinical metric when measuring spinal curves. Using EfficientNetB0 and some transfer learning and data augmentation, we develop a CNN to classify the spinal configuration into lordosis, kyphosis, or neutral. Finally, a rule-based decision system maps the Cobb angle values and the classification results to individualized treatment plans, recommending options such as physiotherapy, bracing, or a surgical consult. The multi-faceted workflow carries its own benefits of providing clinical and research purposes for the assessment of spinal deformities that are efficient, accurate and scalable.

Chapter 6

Results and Discussion

6.1 CNN vs. Transfer Learning for Scoliosis Detction

A custom Convolutional Neural Network (CNN) model was used to differentiate between spinal X-ray images of normal and scoliosis cases. The CNN model produced a validation accuracy of 84.5% and a test accuracy of 87.5%. However, the model showed its inability to properly identify cases of scoliosis, as indicated by a recall of 88.9% on the test set. Misclassification of scoliosis as normal suggested the need for a more robust method to improve diagnostic reliability. Furthermore, the training and validation curves indicated overfitting—while the training accuracy consistently improved and the training loss decreased, the validation accuracy fluctuated and the validation loss began increasing after the initial epochs, implying that the model did not generalize well. This prompted the exploration of a transfer learning approach to enhance model performance.

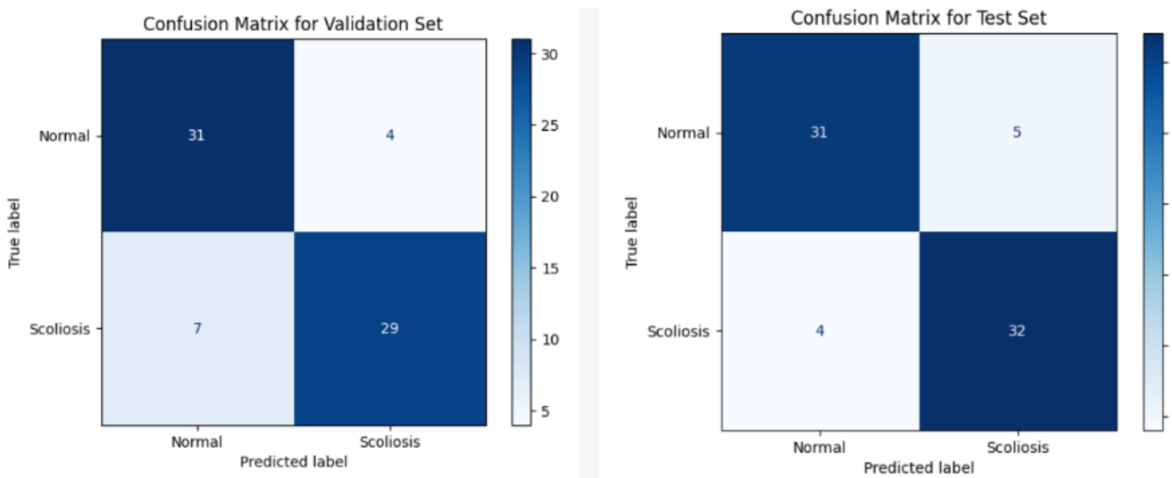


Figure 6.1: Confusion Matrix of CNN model on Validation and Test sets

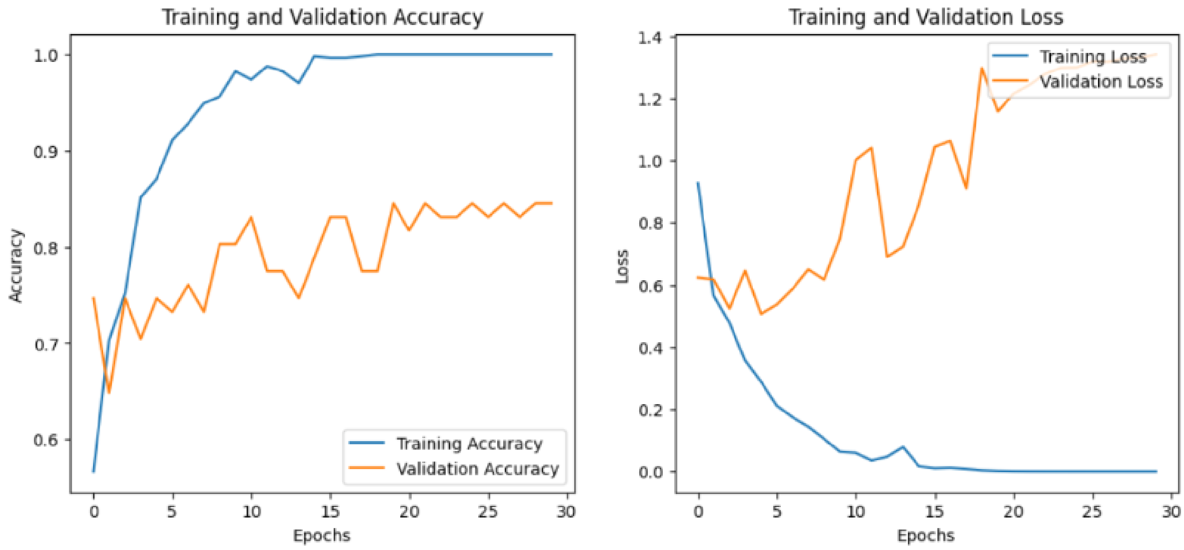


Figure 6.2: Training and validation accuracy/loss plots of CNN Model

To enhance scoliosis detection performance, a Transfer Learning (TL) model with InceptionV3 architecture was applied. The InceptionV3 architecture was found to be superior as it recorded 88.9% accuracy for validation and 95.8% for testing. Further, it even reported 100% recall in case of scoliosis in the test set and thus detection of all cases of scoliosis. Validation curve and training curve had good generalization because the accuracy and the loss remained close together in epochs without the least hint of overfitting.

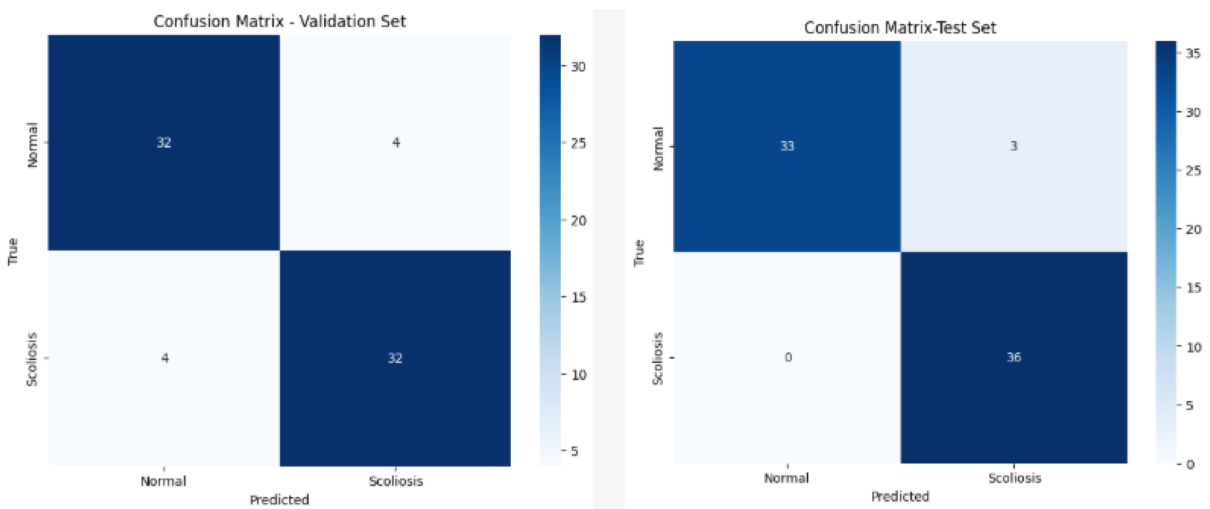


Figure 6.3: Confusion Matrix of TL model on Validation and Test sets

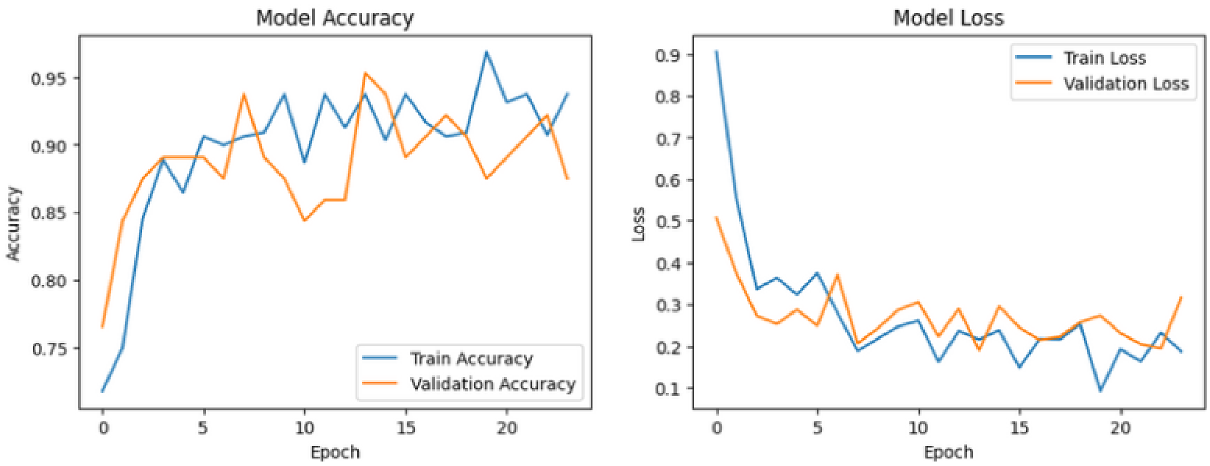


Figure 6.4: Training and validation accuracy/loss plots of TL Model

These performance measurements demonstrate that the Transfer Learning based model using InceptionV3 is more effective and suitable for detecting scoliosis in spinal X-rays than the CNN model.

Metric	**CNN (%)**	**Transfer Learning (%)**
Accuracy	87.50	95.80
Precision	86.50	92.30
Recall	88.90	100.00
F1-Score	87.70	96.00

Table 6.1: Comparison of CNN and Transfer Learning (InceptionV3) Models for Scoliosis Classification

6.2 Postural Deformity Detection using EfficientNetB0

The EfficientNetB0-transfer learning model performed well in classifying images of spinal curvature into classes of kyphosis, lordosis, and normal. The model performed very well for the kyphotic class, accurately classifying all 25 kyphotic images without false classifications. This suggests that the model learned the characteristic differences of kyphotic curvature well. For the normal class, 21 out of 25 images were correctly classified, and 4 were misclassified as lordotic, suggesting that the model was generally reliable but sometimes confused mild curvatures with a normal spine.

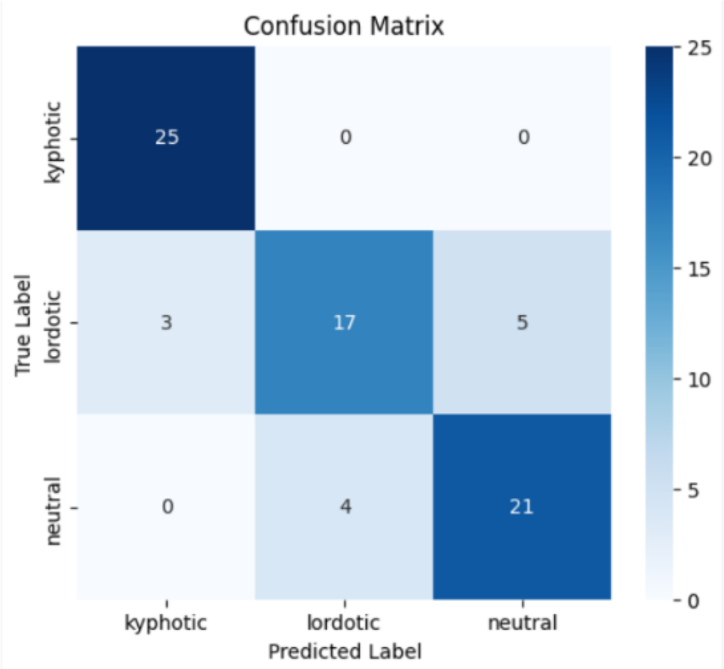


Figure 6.5: Confusion Matrix of TL model using EfficientNetB0

Conversely, the lordotic class exhibited relatively lower accuracy at just 17 correct predictions for 25 samples. The other 8 were misclassified—3 as kyphotic and 5 as normal—and noted the model's inability to accurately distinguish lordosis, likely a result of intersecting visual features or weaker curvature patterns. To counteract this, class weights were used to balance learning and manual corrections were added to manage typical misclassification patterns, particularly those between the neutral class. Overall, the model made effective use of EfficientNetB0's feature extraction, obtaining high precision for kyphotic detection and good overall performance, but with areas to improve in lordosis and neutral class discrimination.

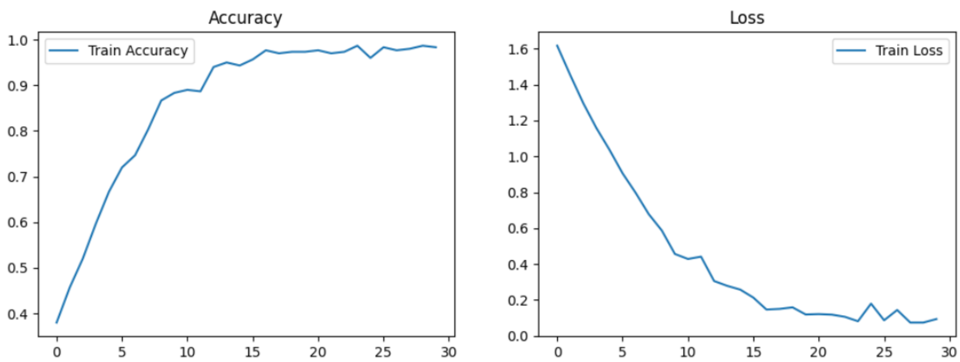


Figure 6.6: Training accuracy/loss plots of TL model using EfficientNetB0

6.3 Chapter Conclusion

The comparative evaluation of deep learning models highlights the significance of selecting an architecture and utilizing transfer learning when detecting spinal disorders. When detecting scoliosis, the CNN model was moderately accurate, but had lower recall and F1-score values, meaning it was not fit-for-purpose to use clinically. The InceptionV3-based transfer learning model was demonstrated to be significant improvement in all performance metrics, ensuring a better detection of true positive cases. Furthermore, for posture classification, MobileNetV2 was unable to accurately classify, yielding moderate accuracy, inconsistently low recall. Switching to the EfficientNetB0 architecture led to large improvements across accuracy, precision, recall, and F1-score, showing an ability to distinguish kyphosis and lordosis and neutral spine. Overall, utilizing transfer learning paired with advanced architectures, transfer learning was essential to provide reliable and accurate automated assessment for spinal disorders.

Chapter 7

Conclusions & Future Scope

The SpineX system provides a practical way to automatically identify and classify spinal deformities (scoliosis, kyphosis, and lordosis). These analyses show that deep learning and transfer learning projects may ultimately lead to improved classification accuracy and diagnostic trust. Significantly, the InceptionV3 model performed better than the personalized CNN in scoliosis detection, with higher accuracy and ideal recall. The transfer learning model with EfficientNetB0 effectively classifies posture deformity diseases such as lordosis and kyphosis. The function and clinical applicability of this system is much improved with Cobb angle estimation and rule-based recommendations for self-management.

Future advancements may emphasize enhancements to detection accuracy by employing advanced deep learning models that reduce false positive results. Using imaging modalities such as three-dimensional MRI and computed tomography (CT) might give more detail in evaluation of the spine. Increasing uptake of mobile and wearable options would give clinicians the ability to continually monitor patients to allow for early detection or intervention. Greater diversity in the datasets would lead to a broader generalizable outcome along with predictive analytics approaches to give personalized recommendations for treatment. Greater integration with electronic health records (EHR) and greater interpretability regarding the analytics would facilitate implementation in a clinical setting and increase health care professional acceptance.

References

[1] H. T. Nguyen, H. H. Pham, N. T. Nguyen, H. Q. Nguyen, T. Q. Huynh, M. Dao, and V. Vu, "Vindr-spinexr: A deep learning framework for spinal lesions detection and classification from radiographs," *MICCAI 2021: 24th International Conference*, pp. 291–301, 2021.

[2] H. Zhang and A. Chung, "A dual coordinate system vertebra landmark detection network with sparse-to-dense vertebral line interpolation," *Bioengineering*, vol. 11, no. 1, p. 101, 2024.

[3] S. Wang, Z. Jiang, H. Yang, X. Li, and Z. Yang, "Automatic segmentation of lumbar spine mri images based on improved attention u-net," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 4259471, 2022.

[4] W. Zhang, Z. Chen, Z. Su, Z. Wang, J. Hai, C. Huang, Y. Wang, B. Yan, and H. Lu, "Deep learning-based detection and classification of lumbar disc herniation on magnetic resonance images," *JOR spine*, vol. 6, no. 3, p. e1276, 2023.

Appendix A: Presentation

SPINEX

AUTOMATED SPINAL AND POSTURE DEFORMITY DETECTION SYSTEM

GUIDE:
MS. MEENU MATHEW

GROUP 8:
NEHA DAVIS
NEHA MARIAM MATHEW
PRIYA ANTO
SHREYA SUNIL

CONTENTS

INTRODUCTION

- Spinal deformities are abnormal curvatures or alignments of the spine that can affect balance, posture, and overall health.
- Common types include:
  - Scoliosis – sideways curvature of the spine.
  - Kyphosis – excessive outward curvature, leading to a hunched back.
  - Lordosis – exaggerated inward curvature of the lower back.

INTRODUCTION

- These conditions may be present at birth, develop during growth, or result from injury, degenerative diseases, or poor posture.
- Symptoms can include back pain, uneven shoulders or hips, restricted movement, and in severe cases, respiratory or neurological issues.
- Early detection and accurate diagnosis are vital to prevent progression and guide appropriate treatment.

PROBLEM STATEMENT

- The traditional diagnosis of spinal deformities relies heavily on manual analysis, which is prone to human error and inconsistencies.
- There is a need for an automated system that can accurately detect, classify, and recommend treatment for conditions like scoliosis, kyphosis, and lordosis to improve diagnostic efficiency and reliability.

PURPOSE AND NEED

- The purpose of the SpineX project is to develop an automated system that enhances the diagnosis and management of spinal deformities using deep learning techniques.
- There is a critical need for such a system to reduce diagnostic time, improve accuracy, and provide consistent, objective results for conditions like scoliosis, kyphosis, and lordosis.

PROJECT OBJECTIVE

- Enhance spinal image quality using image processing techniques.
- Apply deep learning models to detect spinal deformity like scoliosis.
- Automate keypoint detection and enable manual refinement to assess spinal curvature using Cobbs Angle Measurement.
- Evaluate spinal deformity severity and recommend appropriate treatment.
- Identify postural abnormalities using advanced convolutional models and suggest treatments.

LITERATURE SURVEY

Name of the Author(s)	Methods Used	Advantages	Disadvantages
Nguyen et al. (2021)	Convolutional Neural Networks (CNNs), Attention Mechanisms	High accuracy in lesion localization and classification in spinal X-rays.	Requires a large, annotated dataset for training, which may not always be available.
Zhang and Chung (2024)	Transformer-based Network, Multi-scale Feature Fusion	Improved precision and robustness in vertebra landmark localization.	The complex architecture may demand high computational resources.
Wang et al. (2022)	U-Net with Dense Connections, Data Augmentation	Enhanced segmentation performance in complex or noisy MRI images.	Needs a large amount of annotated data for effective model training.
Zhang et al. (2023)	Deep CNN with Residual Blocks, Transfer Learning	High accuracy in detecting and classifying lumbar disc herniation.	Performance can vary depending on the quality and diversity of MRI data used for training.

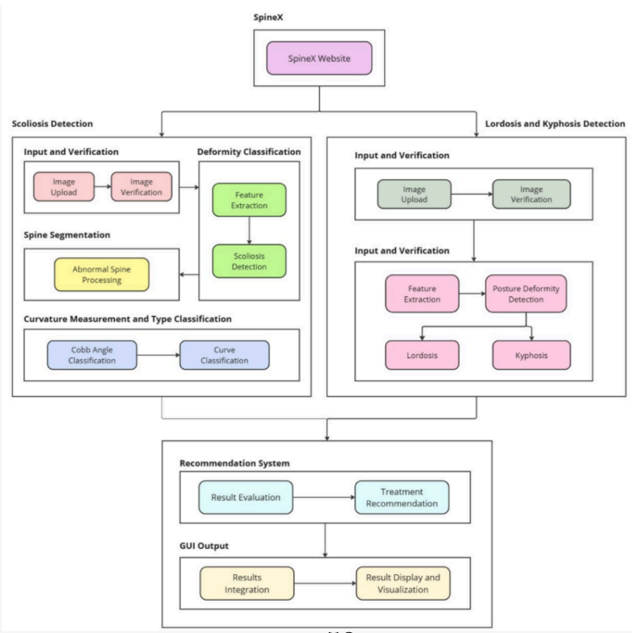
PROPOSED METHOD

- Collect and preprocess spinal X-ray images of both normal and scoliosis cases using image enhancement techniques.
- Train a CNN model and a Transfer Learning model with InceptionV3 as the base to classify X-rays into scoliosis or normal categories with improved accuracy.
- Apply spinal segmentation to automatically detect keypoints along the spine, with an option for manual refinement to ensure precise Cobb angle measurement and identify the curvature type for severity assessment.

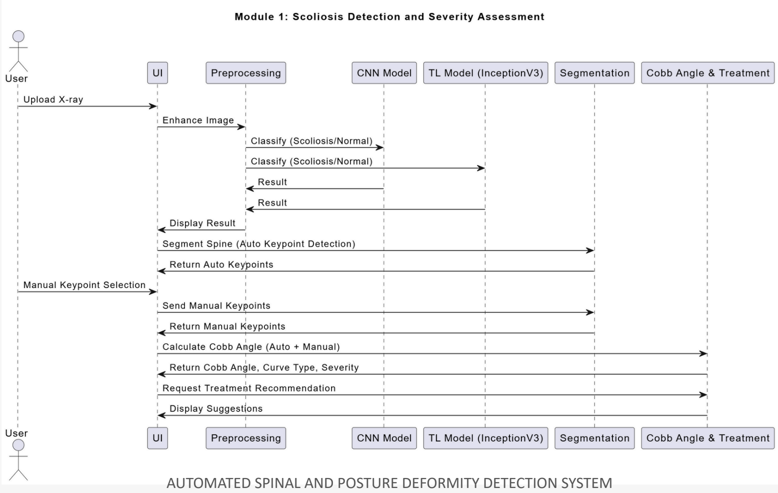
PROPOSED METHOD

- Assess scoliosis severity and generate treatment recommendations based on Cobb angle measured and the curvature type detected.
- Collect and preprocess side-view posture images for deformity analysis.
- Use a Transfer Learning model based on EfficientNetB0 to classify posture images into lordosis, kyphosis, or normal, and suggest appropriate corrective measures or treatments.

ARCHITECTURE DIAGRAM



SEQUENCE DIAGRAM



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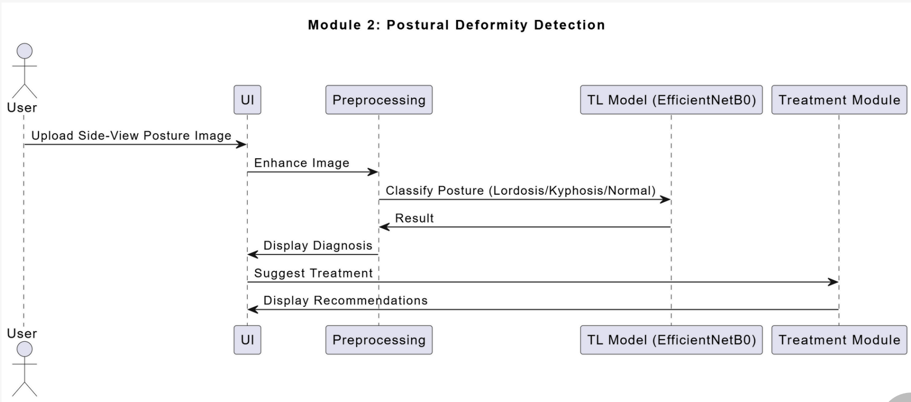
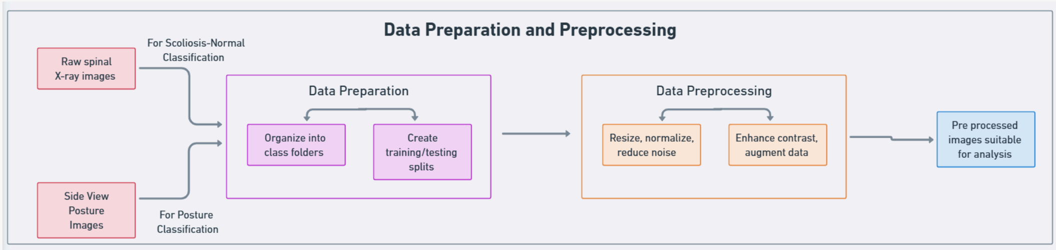


MODULES

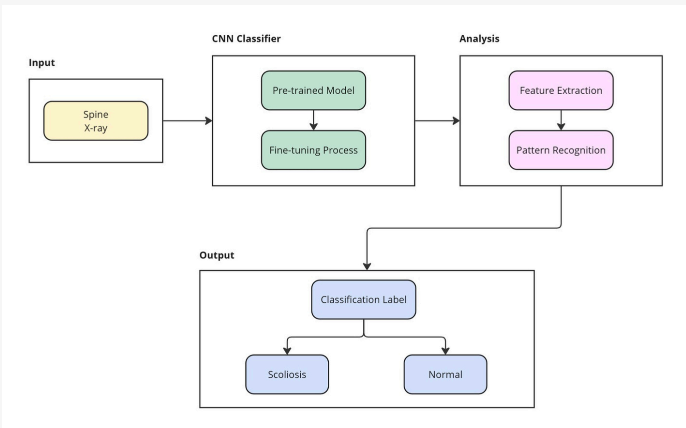
- **Data Collection & Preparation**
- **Spinal Deformity Classification**
- **Spine Segmentation**
- **Curvature Measurement & Curve Type Classification**
- **Posture Deformity Detection**
- **Treatment Guidance & User Interface**

1. DATA PREPARATION AND PREPROCESSING



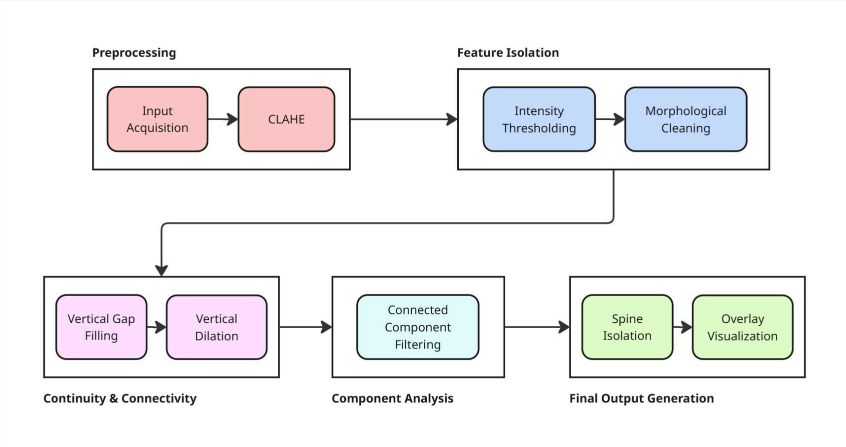
- Obtain X-ray images for Scoliosis classification and side-view posture images for Spine Deformity classification.
- Resize images, convert to grayscale, and normalize pixel values.
- Apply data augmentation techniques like rotation, flipping, and zooming.
- Organize X-ray images into two folders: Normal and Scoliosis. Organize posture images into three folders: Neutral, Lordosis, and Kyphosis.
- Split the dataset into 80% training, 10% validation, and 10% testing.

2. SPINAL DEFORMITY CLASSIFICATION



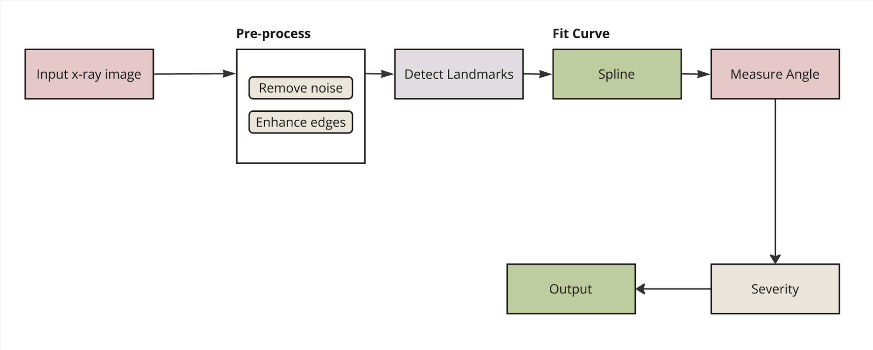
- Developed two models for scoliosis detection from X-ray images:
  - A custom CNN model trained from scratch to learn spatial features specific to spinal curvature.
  - A Transfer Learning model using InceptionV3 as the base, leveraging pre-trained weights for improved generalization on limited medical data.
- Both models classify X-ray images into scoliosis and normal categories.
- Evaluated model performance using accuracy, precision, recall, and confusion matrices to compare effectiveness.

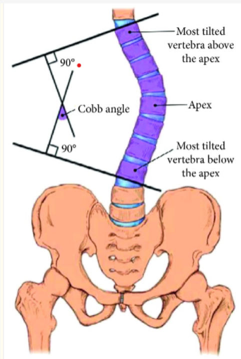
3. SPINE SEGMENTATION



- The X-ray image is first enhanced using CLAHE to improve contrast and highlight bone structures.
- A central vertical region is extracted and thresholded to isolate the spine area.
- Morphological operations and vertical continuity checks are applied to clean and connect the spine.
- The spine is isolated using component filtering and visualized with an overlay on the original image.
- Segmentation aids in automatically detecting keypoints along the spine, which are essential for assessing spinal curvature using Cobb’s angle .

4. CURVATURE MEASUREMENT & CURVE TYPE CLASSIFICATION

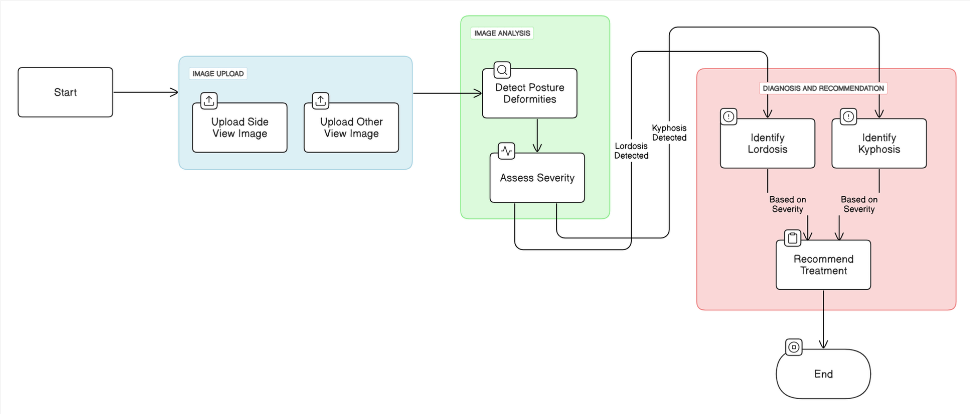




Cobb angle	Definition
0°–10°	Spinal curve
10°–20°	Mild scoliosis
20°–40°	Moderate scoliosis
>40°	Severe scoliosis

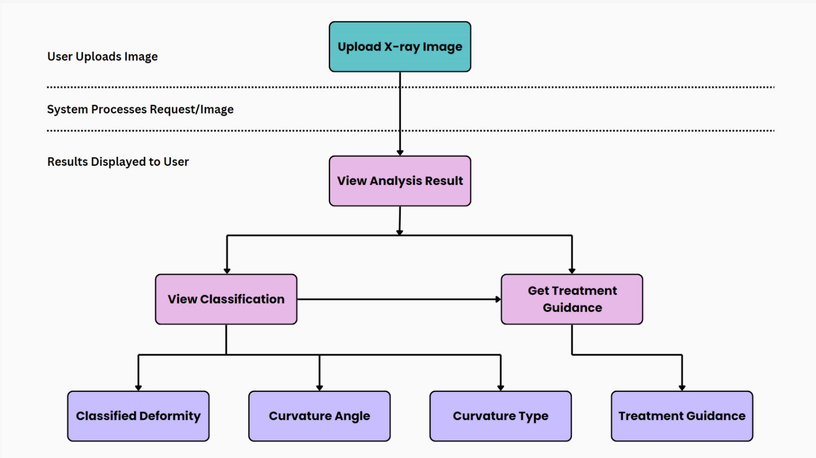
- Once scoliosis is detected, keypoints along the spine are extracted to trace its alignment.
- Using these keypoints, the Cobb's angle is calculated by identifying the most tilted vertebrae and measuring the angle between them.
- Based on the pattern of the spinal curve, the type of curvature is classified as C-shaped or S-shaped curve.
- The severity of scoliosis is determined using Cobb's angle measured and classifies severity into: mild, moderate, or severe.

5. POSTURE DEFORMITY DETECTION



- A labeled dataset with subfolders for lordosis, kyphosis, and neutral postures is used to train the model.
- The images are preprocessed (resized, normalized, and enhanced) to improve model accuracy and consistency.
- The trained model then detects posture deformities, including lordosis and kyphosis, from the uploaded images.
- It supports accurate diagnosis and treatment recommendations by evaluating the presence of lordosis and kyphosis.

6. TREATMENT GUIDANCE & USER INTERFACE



- Provides AI-driven treatment guidance, such as exercises and lifestyle tips for spine deformities.
- It also provides a user-friendly platform for uploading images, allowing users to easily access their results and treatment guidance in a straightforward manner.

ASSUMPTIONS

- **Sufficient Dataset Diversity:** It is assumed that the dataset includes a diverse range of spinal X-ray images, encompassing various deformities and normal cases, to ensure robust model training and accurate classification.
- **Adequate Computational Resources:** It is assumed that the project will have access to sufficient computational resources to support the training and deployment of deep learning models effectively.

WORK BREAKDOWN AND RESPONSIBILITIES

Neha Davis

Deformity Classification and Analysis

Neha Mariam Mathew

Data Collection & Preprocessing and GUI

Priya Anto

Model Development & Segmentation

Shreya Sunil

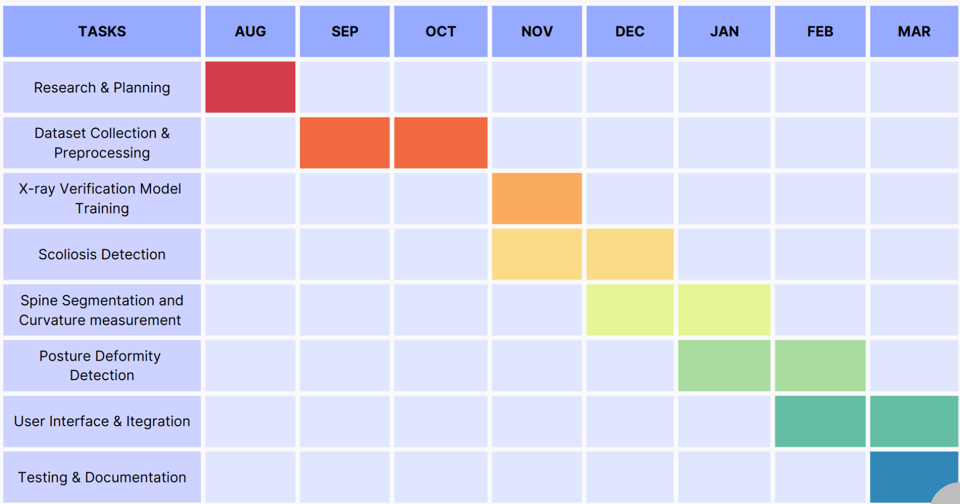
Model Optimization & Angle Measurement

HARDWARE AND SOFTWARE REQUIREMENTS

HARDWARE REQUIREMENTS	SOFTWARE REQUIREMENTS

• **GPU:** NVIDIA GPU (Tesla, Quadro, or GTX) with CUDA support (Minimum 8GB VRAM recommended).
• **CPU:** Multi-core processor (Intel i7 or higher, or AMD equivalent).
• **RAM:** Minimum 16GB.
• **Storage:** SSD with at least 100GB free space for storing datasets and models.
• **Operating System:** Linux (Ubuntu preferred) or Windows 10/11
	• **OS:** Windows 10 or Ubuntu 20.04
	• **Languages:** Python 3.x
	• **Libraries:**
	  ◦ TensorFlow/Keras or PyTorch (ML)
	  ◦ OpenCV (image processing)
	  ◦ NumPy, SciPy (calculations)
	  ◦ SciKit-Learn (classification)
	• **Framework:** Flask
	• **CUDA:** Required for GPU acceleration with TensorFlow or PyTorch.

GANTT CHART



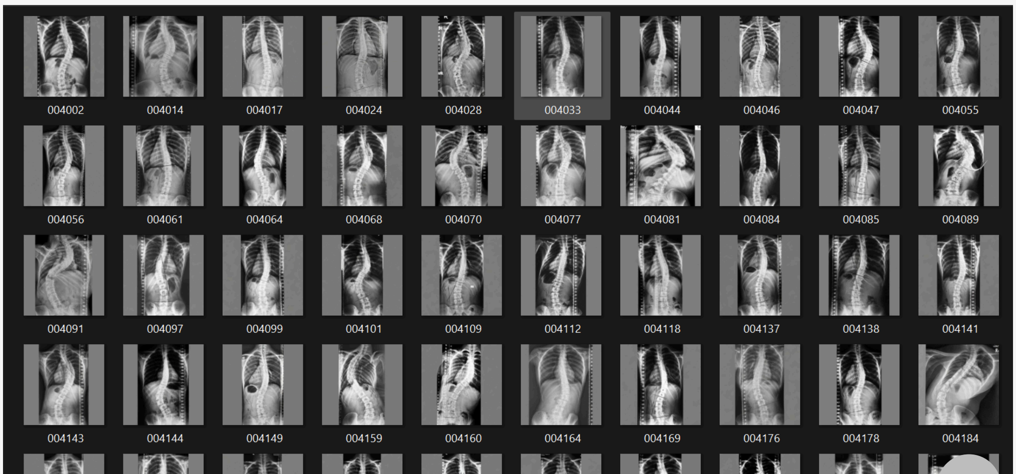
RISKS AND CHALLENGES

- **Data Quality and Availability**: Obtaining a diverse, high-quality X-ray dataset for training is challenging due to privacy issues and limited access to labeled medical data.
- **Model Accuracy and Reliability**: Achieving high accuracy is critical, as misclassifications can affect diagnosis and treatment, posing risks to patient care.
- **Integration with Existing Systems**: Integrating the system with hospital workflows and adhering to medical standards can be complex and time-consuming.
- **Adoption by Healthcare Professionals**: Gaining trust and acceptance from doctors and radiologists may be challenging, as they may prefer traditional diagnostic methods.

Scoliosis Detection Module

DATASET PREPARATION

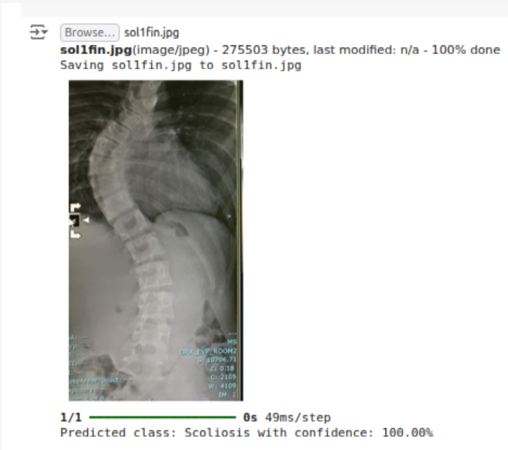
- **Data Sources:**
  - Primary dataset from Kaggle (The vertebrae X-ray images).
  - Additional dataset manually split into scoliosis and normal categories.
- **Data Augmentation:**
  - Applied to increase and balance the distribution between normal and scoliosis classes. Augmented with `ImageDataGenerator`.
- **Data Splitting:**
  - Training: 80%
  - Validation: 10%
  - Testing: 10%
- **Purpose:**
  - Ensures a balanced dataset for effective model training and evaluation.

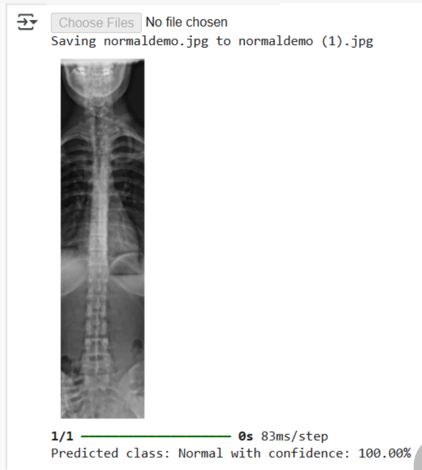


CNN MODEL

- **Preprocessing:**
  - Images resized to 224x224 and normalized.
- **Model:**
  - CNN with 3 convolutional layers, max-pooling, and fully connected layers.
  - Flattening layer
  - Output layer with softmax for multi-class classification.
- **Evaluation:**
  - Accuracy and loss on the validation set.
  - Confusion matrix visualized.
- **Visualization:**
  - Accuracy and loss plots.

OUTPUT





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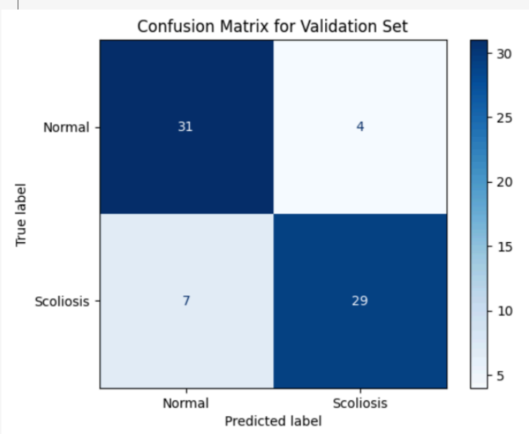
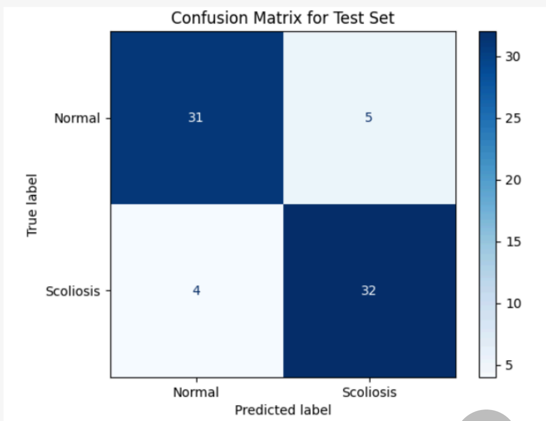


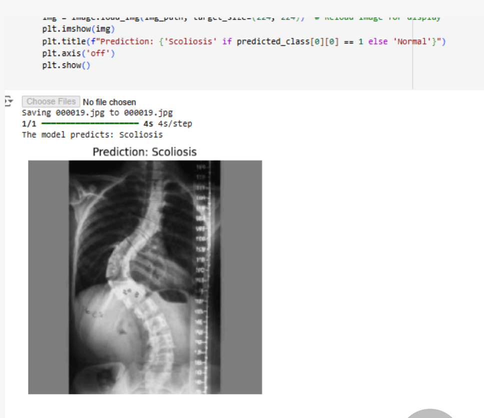


OUTPUT

TRANSFER LEARNING

- **Model Architecture:**
  - Base: InceptionV3 (pre-trained).
  - Custom layers: GlobalAveragePooling, Dense, Dropout, Sigmoid for binary classification.
- **Training:**
  - Optimizer: Adam, Loss: binary cross-entropy, Metric: accuracy.
  - Callbacks: EarlyStopping and ModelCheckpoint.
- **Evaluation:**
  - Test accuracy and loss.
  - Classification report and confusion matrix.
- **Visualization:**
  - Accuracy/loss plots, confusion matrix heatmap.

OUTPUT



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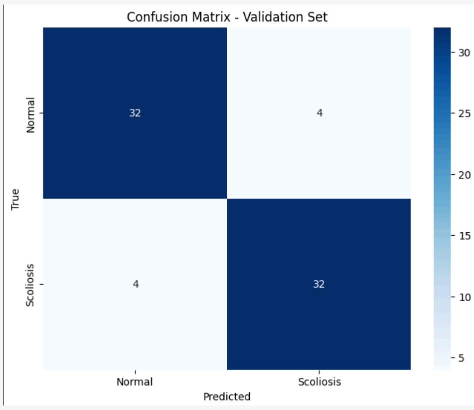
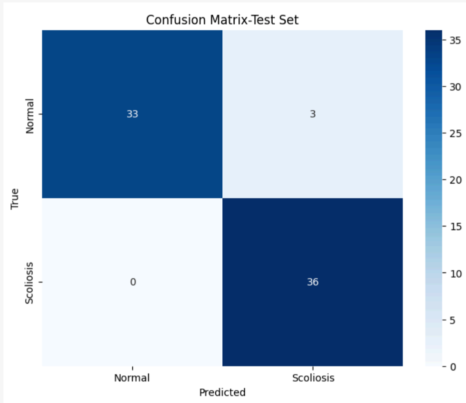
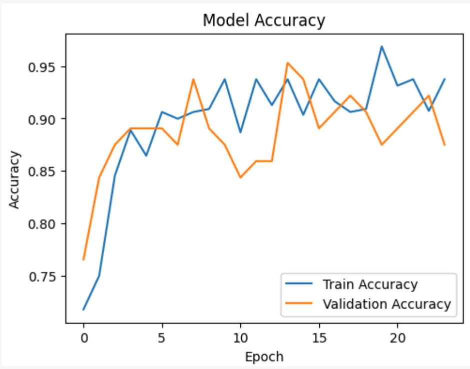
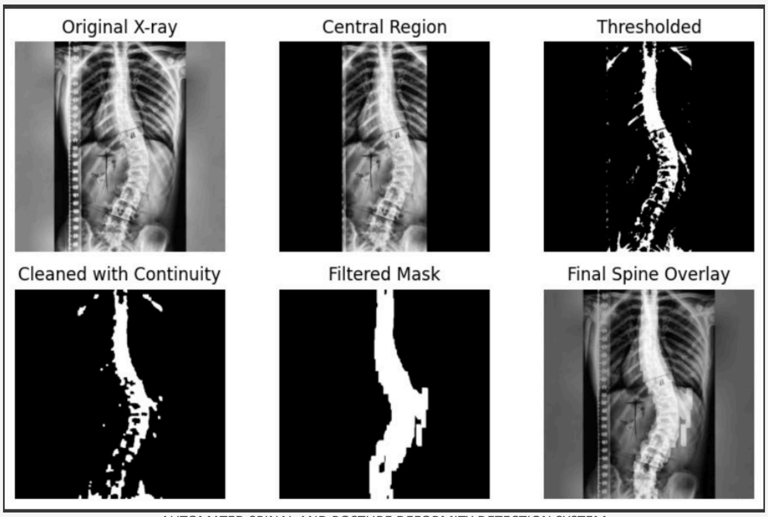




OUTPUT



SPINE SEGMENTATION



SPINE SEGMENTATION

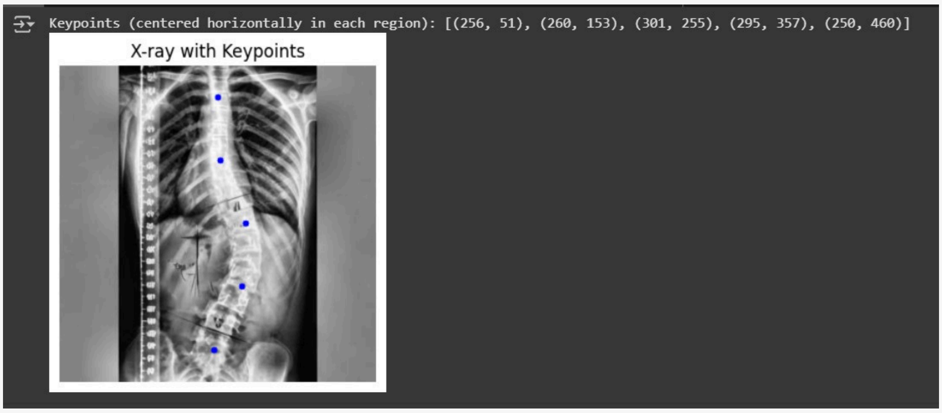
1. **Preprocessing and Thresholding**: The central region of the X-ray is focused on using a vertical mask, followed by intensity thresholding to isolate the spine.

2. **Morphological Operations**: Noise is removed, and fragmented parts of the spine are connected using morphological operations, ensuring continuity.

3. **Gap Filling and Dilation**: Gaps in the spine are filled, and dilation connects distant spine regions to capture the full structure.

4. **Component Filtering and Final Masking**: Small irrelevant components are filtered out, and the refined mask isolates the spine, which is then overlaid on the original image for better visualization.

GENERATING KEY POINTS ALONG THE MASK



COBB ANGLE MEASUREMENT AND SEVERITY CLASSSIFICATION

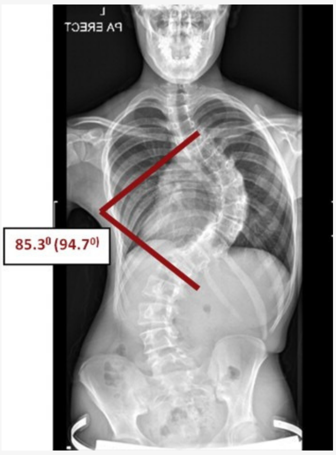
1. **Click to Select Points**: Users click on five vertebrae points in the uploaded image to help accurately calculate the Cobb angle.

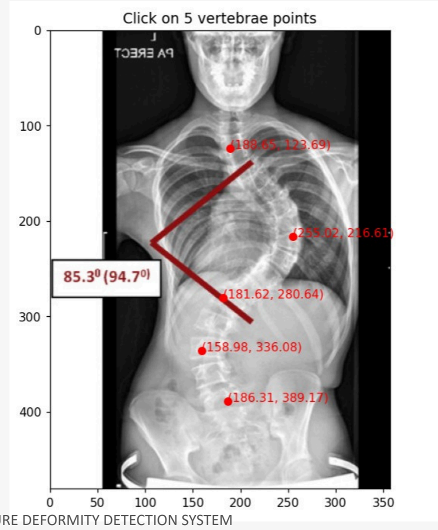
2. **Cobb Angle Calculation**: The code computes the Cobb angle from the selected points.

3. **Curve Classification**: Based on the Cobb angle, the curve is classified as S-shaped or C-shaped.

4. **Severity Assessment**: The severity of scoliosis (mild, moderate, or severe) is determined with treatment recommendations.

COBB ANGLE MEASUREMENT FOR A S-CURVE

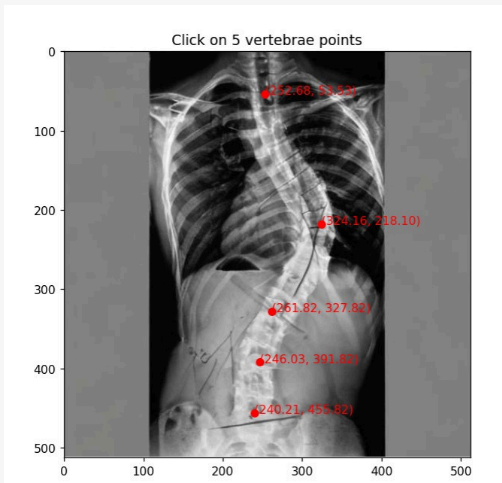




COBB ANGLE AND SEVERITY CLASSSIFICATION FOR A S-SHAPED CURVE

```
Clicked: (188.65, 123.69)
Clicked: (255.02, 216.61)
Clicked: (181.62, 280.64)
Clicked: (158.98, 336.08)
Clicked: (186.31, 389.17)
Five points clicked. Processing Cobb Angle...
Top Cobb Angle: 84.44°
Bottom Cobb Angle: 49.45°
Maximum Cobb Angle: 84.44°
Curve Type: S-shaped curve
Severity:
Severe scoliosis: Cobb angle of more than 40 degrees.
Spinal fusion surgery may be required to correct the curve.
```


COBB ANGLE MEASUREMENT FOR A C-CURVE

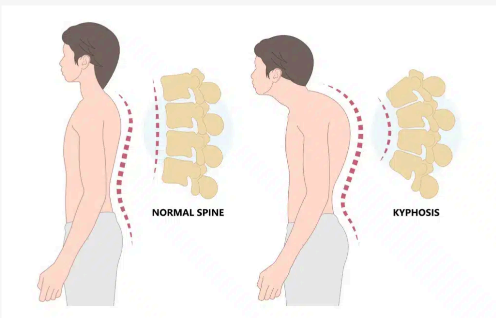


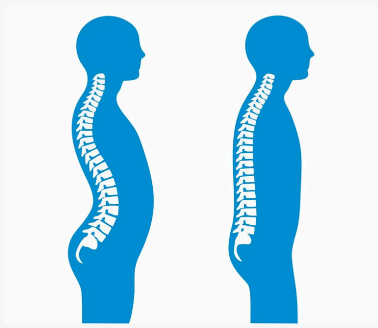
COBB ANGLE AND SEVERITY CLASSSIFICATION FOR A C-SHAPED CURVE

```
Clicked: (252.68, 53.53)
Clicked: (324.16, 218.10)
Clicked: (261.82, 327.82)
Clicked: (246.03, 391.82)
Clicked: (240.21, 455.82)
Five points clicked. Processing Cobb Angle...
Top Cobb Angle: 53.08°
Bottom Cobb Angle: 8.67°
Maximum Cobb Angle: 53.08°
Curve Type: C-shaped curve
Severity:
Severe scoliosis: Cobb angle of more than 40 degrees.
Spinal fusion surgery may be required to correct the curve.
```


Posture Deformity Detection Module

WHAT IS KYPHOSIS & LORDOSIS?





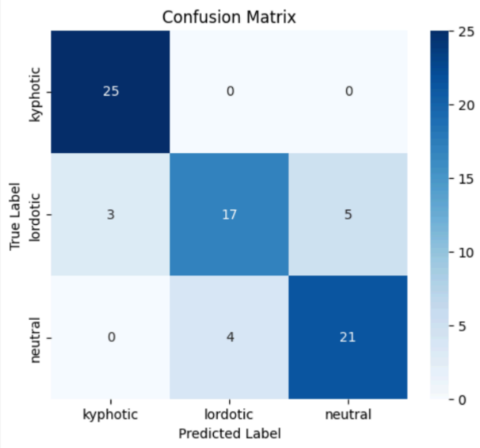
MODEL WORKFLOW

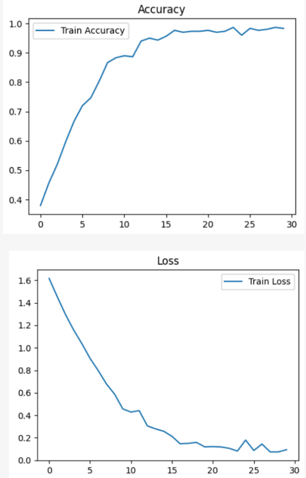
- **Data Preprocessing & Augmentation**
  - Loads images from /content/LordKyph with rotation, shift, zoom, flip.
  - Splits dataset: 80% training, 20% validation.
- **Model Architecture**
  - Base Model: EfficientNetB0 (pre-trained, frozen weights).
    - Added Layers:Global Average Pooling
    - Dense (128, ReLU) → Dropout (0.5)
    - Dense (3, Softmax) → 3-class classification.

TRAINING & EVALUATION

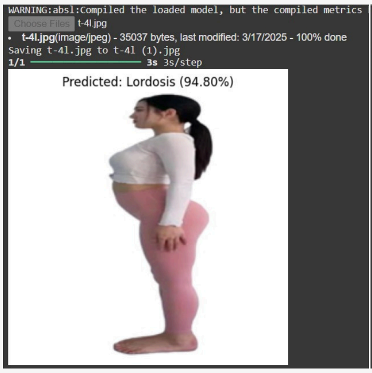
- **Compilation & Training**
  - Optimizer: Adam
  - Loss Function: Categorical Crossentropy
  - Metric: Accuracy
  - Trained for 30 epochs on augmented data.
- **Model Saving, Testing & Evaluation**
  - Saves model as lordkyph_classifier.h5.
  - Loads saved model for evaluation.
  - Tests on a separate dataset & prints test accuracy.
  - Plots accuracy & loss curves for performance analysis.

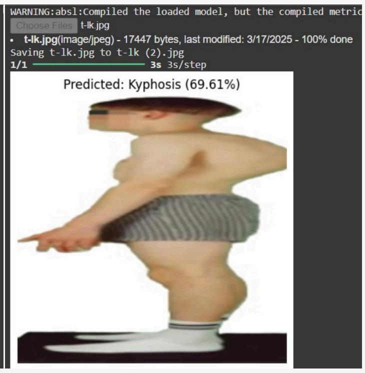
OUTPUT

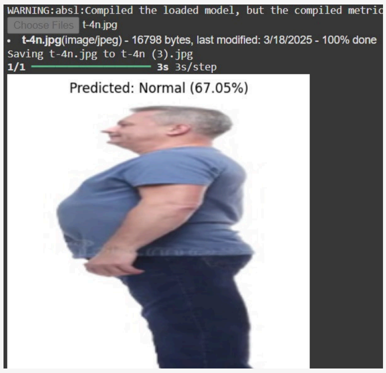




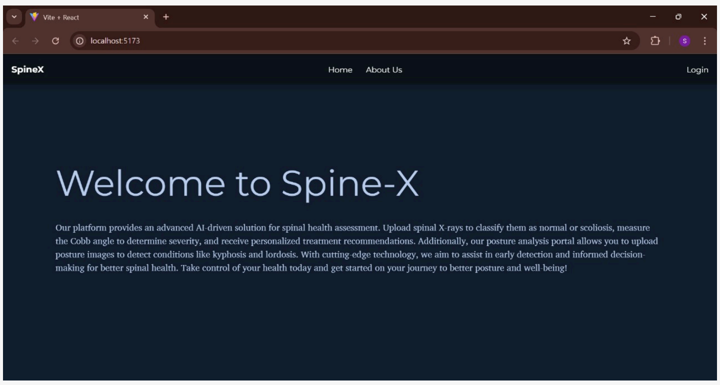
OUTPUT

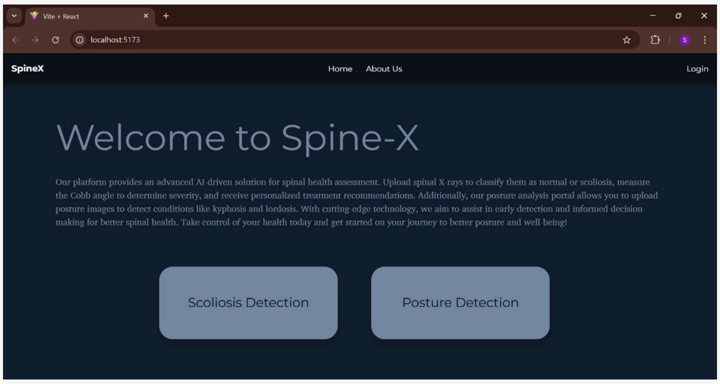






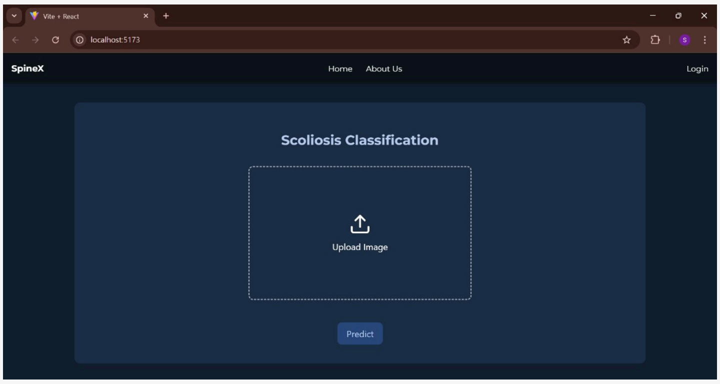
User Interfaces





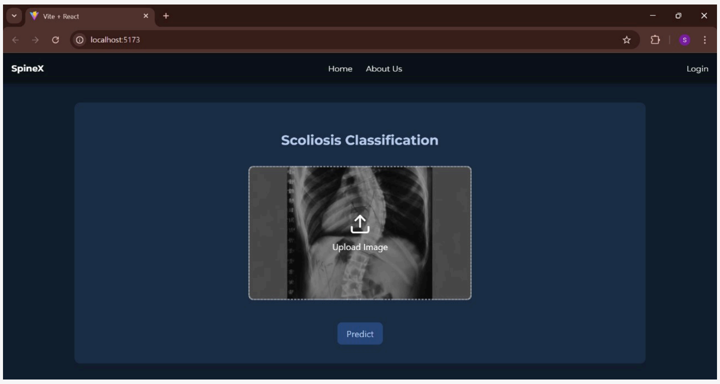
AUTOMATED SPINAL AND POSTURE DEFORMITY DETECTION SYSTEM

59



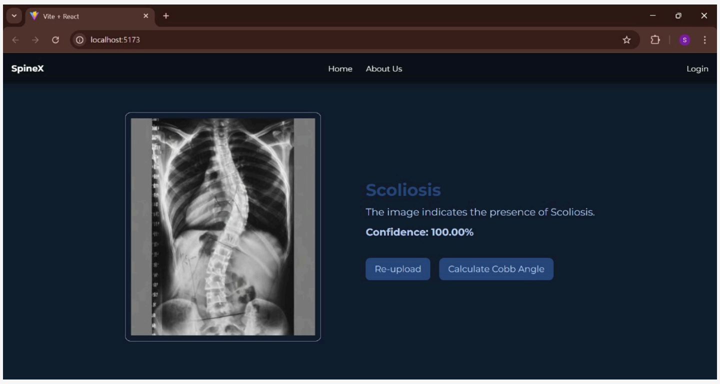
AUTOMATED SPINAL AND POSTURE DEFORMITY DETECTION SYSTEM

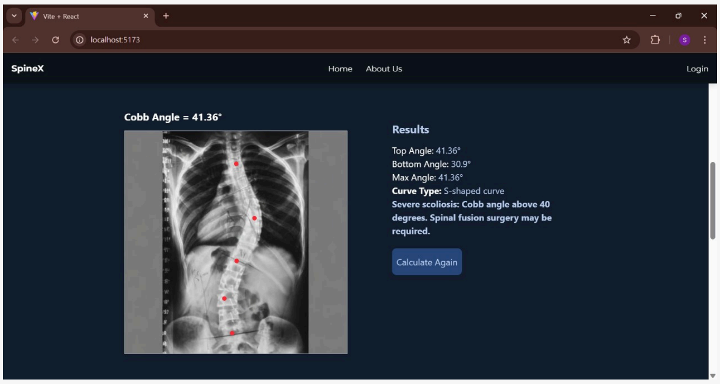
60

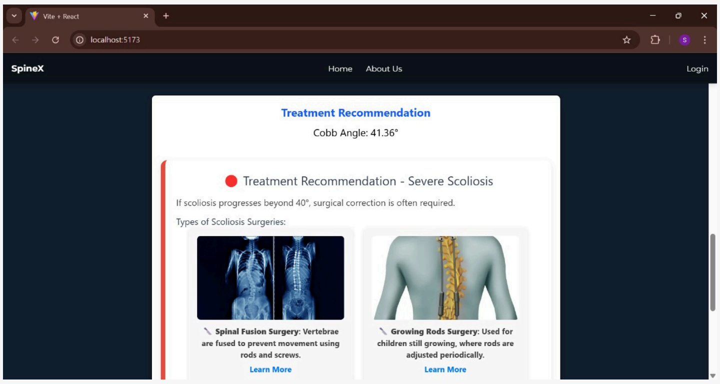


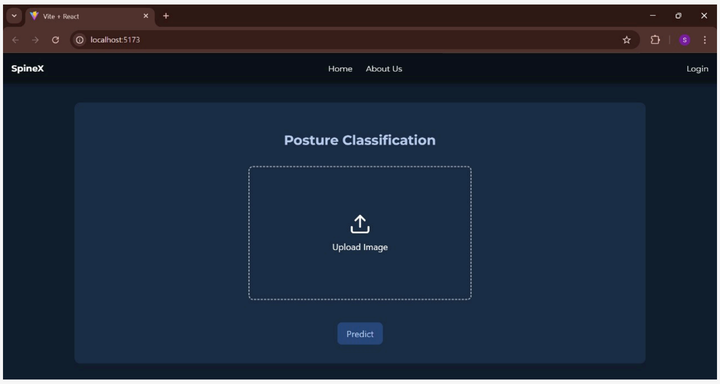
AUTOMATED SPINAL AND POSTURE DEFORMITY DETECTION SYSTEM

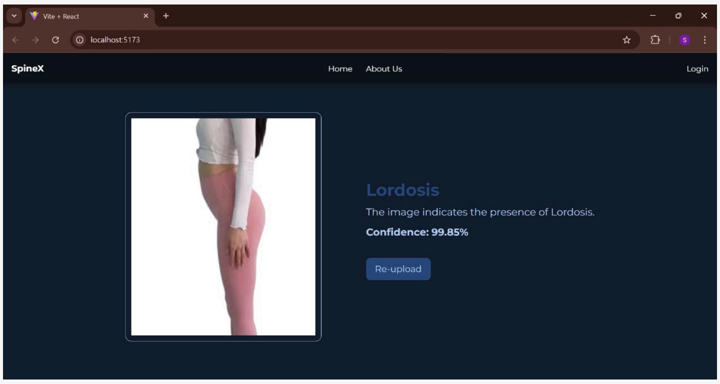
61

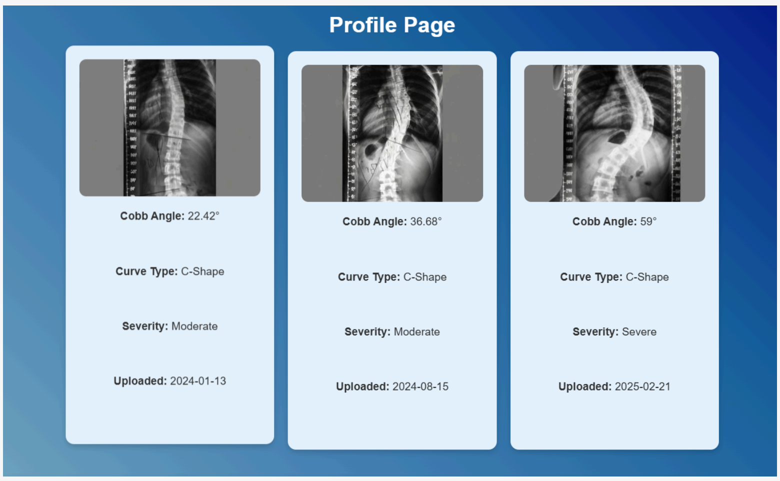

Vite + React
localhost:5173
SpineX
Home
About Us
Login
Scoliosis
The image indicates the presence of Scoliosis.
Confidence: 100.00%
Re-upload
Calculate Cobb Angle

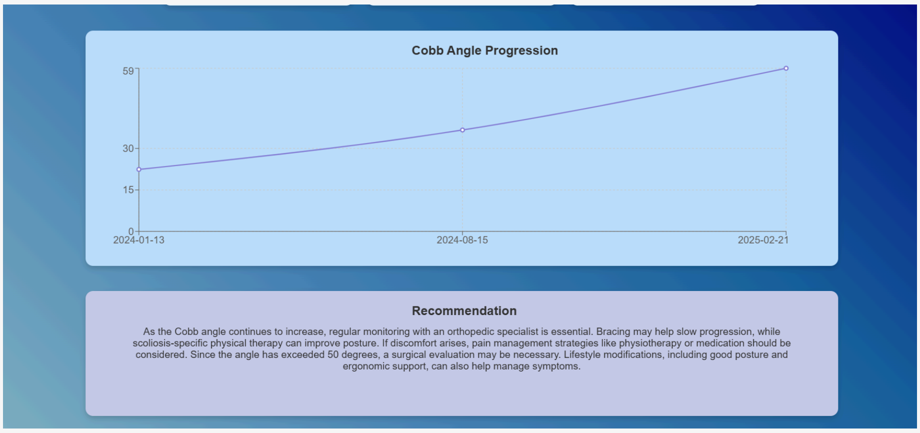

Vite + React
localhost:5173
SpineX
Home
About Us
Login
Cobb Angle = 41.36°
Results
Top Angle: 41.36°
Bottom Angle: 30.9°
Max Angle: 41.36°
Curve Type: S-shaped curve
Severe scoliosis: Cobb angle above 40 degrees. Spinal fusion surgery may be required.
Calculate Again

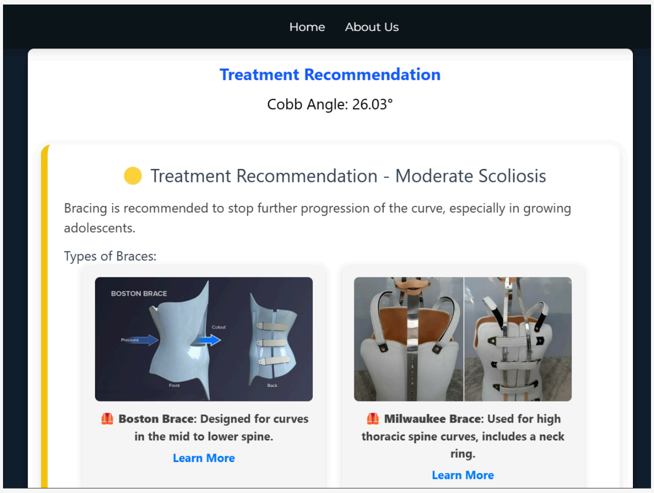

Vite + React
localhost:5173
SpineX
Home
About Us
Login
Treatment Recommendation
Cobb Angle: 41.36°
Treatment Recommendation - Severe Scoliosis
If scoliosis progresses beyond 40°, surgical correction is often required.
Types of Scoliosis Surgeries:
Spinal Fusion Surgery: Vertebrae are fused to prevent movement using rods and screws.
Learn More
Growing Rods Surgery: Used for children still growing, where rods are adjusted periodically.
Learn More


Vite + React
localhost:5173
SpineX
Home
About Us
Login
Posture Classification
Upload Image
Predict


Vite + React
localhost:5173
SpineX
Home
About Us
Login
Lordosis
The image indicates the presence of Lordosis.
Confidence: 99.85%
Re-upload


Profile Page
Cobb Angle: 22.42°
Curve Type: C-Shape
Severity: Moderate
Uploaded: 2024-01-13
Cobb Angle: 36.68°
Curve Type: C-Shape
Severity: Moderate
Uploaded: 2024-08-15
Cobb Angle: 59°
Curve Type: C-Shape
Severity: Severe
Uploaded: 2025-02-21





FUTURE WORK

- Expand Dataset Diversity for Generalization: Increasing the size and diversity of datasets will improve the model's ability to generalize across different patient populations, making the system more reliable and effective in real-world clinical settings.

- Real-Time Integration into Clinical Workflows: Implementing the system for real-time use will streamline clinical workflows, providing physicians with immediate insights and AI-assisted treatment recommendations that support faster, more accurate decision-making in diagnosing and managing spinal deformities.

CONCLUSION

- This project aims to improve the diagnosis of spinal deformities, including scoliosis, kyphosis and lordosis through advanced deep learning models.
- By automating the detection and classification of these conditions, it supports healthcare professionals in providing quicker and more accurate assessments. This solution enhances patient care by reducing diagnostic time and offering consistent, reliable analysis.

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Nguyen, H. T., Pham, H. H., Nguyen, N. T., Nguyen, H. Q., Huynh, T. Q., Dao, M., & Vu, V. (2021). VinDr-SpineXR: A deep learning framework for spinal lesions detection and classification from radiographs. MICCAI 2021: 24th International Conference (pp. 291-301). Springer

Zhang, H. and Chung, A.C., 2024. A Dual Coordinate System Vertebra Landmark Detection Network with Sparse-to-Dense Vertebral Line Interpolation. Bioengineering, 11(1), p.101.

Wang, S., Jiang, Z., Yang, H., Li, X. and Yang, Z., 2022. Automatic segmentation of lumbar spine MRI images based on improved attention U-net. Computational Intelligence and Neuroscience, 2022(1), p.4259471.

Zhang, W., Chen, Z., Su, Z., Wang, Z., Hai, J., Huang, C., Wang, Y., Yan, B. and Lu, H., 2023. Deep learning-based detection and classification of lumbar disc herniation on magnetic resonance images. JOR spine, 6(3), p.e1276.

THANK YOU

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision
To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission
To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision
To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission
To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)
Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

After the completion of the course the student will be able to:

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

COURSE OUTCOMES:

After completion of the course, the student will be able to:

SL.NO	DESCRIPTION	Bloom's Taxonomy Level
CO1	Model and solve real-world problems by applying knowledge across domains (Cognitive knowledge level:Apply).	Level3: Apply
CO2	Develop products, processes, or technologies for sustainable and socially relevant applications. (Cognitive knowledge level:Apply).	Level 3: Apply
CO3	Function effectively as an individual and as a leader in diverse teams and comprehend and execute designated tasks. (Cognitive knowledge level:Apply).	Level 3: Apply
CO4	Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level:Apply).	Level 3: Apply
CO5	Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level:Analyze).	Level 4: Analyze
CO6	Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level:Apply).	Level 3: Apply

CO-PO AND CO-PSO MAPPING

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	3	3	2	2	3	2	1	1	2	2	1	2	3	2	2
CO2	3	3	3	3	3	2	2	1	3	2	2	2	3	3	3
CO3	3	2	3	3	2	2	1	1	2	2	2	2	3	3	3
CO4	2	2	3	2	3	3	2	2	3	3	2	2	3	3	2
CO5	3	3	3	3	3	3	2	2	3	3	2	3	3	3	3
CO6	2	2	2	2	2	2	2	1	3	3	2	2	3	3	2

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

Mapping	**Level**	**Justification**
101003/CS822U.1-PO1	M	Application of fundamental concepts in image processing, deep learning, and anatomy to develop an automated spinal disease detection system.
101003/CS822U.1-PO2	M	Ability to identify challenges in spinal deformity diagnosis, analyze medical datasets, and derive meaningful conclusions from model outputs.
101003/CS822U.1-PO3	M	Designing an end-to-end solution for medical diagnosis using segmentation and classification techniques tailored to spinal X-ray images.
101003/CS822U.1-PO4	M	Investigation of model performance using validation metrics like accuracy and Cobb angle measurement for medical relevance.
101003/CS822U.1-PO5	H	Leveraging advanced tools such as CNNs, Python libraries, and annotation platforms to implement and evaluate the detection pipeline.
101003/CS822U.1-PO6	M	Understanding the societal impact of early spinal disease detection and its role in improving patient outcomes.
101003/CS822U.1-PO7	M	Incorporation of sustainable computing practices and resource-aware model training.
101003/CS822U.1-PO8	L	Respecting patient data privacy and ethical considerations in healthcare-based model development.
101003/CS822U.1-PO9	L	Coordination with peers for tasks such as dataset preparation, model training, and report writing.
101003/CS822U.1-PO10	M	Clear documentation and presentation of the methodology, results, and medical significance of the SPINEX project.
101003/CS822U.1-PO11	H	Applying project management strategies to handle data acquisition, model evaluation, and integration stages effectively.

101003/CS822U.1-PO12	H	Adapting to emerging medical imaging technologies and learning new techniques for continuous skill development.
101003/CS822U.1-PSO1	H	Utilization of computer science fundamentals to automate diagnosis of scoliosis, kyphosis, and lordosis.
101003/CS822U.2-PSO2	M	Developing solutions that can contribute to affordable and early healthcare diagnosis in underserved regions.
101003/CS822U.3-PSO3	H	Promoting collaboration across software and healthcare domains to deliver a socially impactful system.
101003/CS822U.4-PSO3	H	Structured planning, from problem definition to deployment, enabled efficient progress tracking in the SPINEX project.
101003/CS822U.5-PSO1	H	Applying programming, machine learning, and domain knowledge to build an innovative, functional solution.
101003/CS822U.6-PSO3	H	Effective communication of technical details and medical insights through visualizations, presentations, and reports.