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Scoliosis Detection: Edge-Preserving Preprocessing of Spinal X-Rays Using PDEs and Deep Learning-Based Classification

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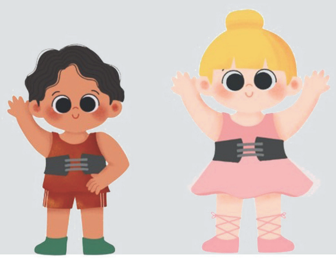


Abstract

Scoliosis is an abnormal spinal curvature, commonly affecting adolescents during peak bone growth. Early detection of Adolescent Idiopathic Scoliosis (AIS) enables non-surgical treatments like physiotherapy and braces (e.g., Boston Brace, Milwaukee Brace). This research proposes an innovative approach to enhance the accuracy of spinal X-ray image analysis. We aim to improve image quality and diagnostic accuracy by combining the power of Partial Differential Equations (PDEs), specifically the Heat Equation and Anisotropic Diffusion, for pre-processing and a Convolutional Neural Network (CNN) for classification. The pre-processing stage reduces noise and preserves fine details, while CNN classifies images as normal or indicative of scoliosis. We expect significant improvements in noise reduction, and edge preservation, leading to higher classification accuracy and aiding in early diagnosis and efficient treatment planning for scoliosis.

Introduction

Scoliosis, a 3D spinal deformity, affects 3% of adolescents under 16, with Adolescent Idiopathic Scoliosis accounting for 80% of pediatric cases. Accurate diagnosis and treatment often require detailed spinal curvature analysis, often requiring medical imaging like X-rays. Noise in X-ray images can obscure critical features, and traditional denoising techniques can blur essential edges.

This research proposes a novel method for enhancing X-ray image quality and accuracy in scoliosis detection. The method uses the Heat Equation, Partial Differential Equation (PDE), and edge preservation with Anisotropic Diffusion to reduce noise and classify X-rays as "normal" or "scoliosis."

This approach aims to develop an efficient system for early scoliosis detection, improving diagnosis, treatment planning, and patient outcomes.

Mathematical Modelling

1.Using Partial Differential Equations (PDEs) for Pre-processing Stage :

Heat Equation for Noise Reduction:

The heat equation, a partial differential equation, models intensity diffusion in images by treating pixel values like temperatures.

$$\frac{\partial u}{\partial t} = \alpha \nabla^2 u$$

Raju, I., et al. (2022)

Anisotropic Diffusion for Preprocessing:

Anisotropic diffusion is a nonlinear filtering method that reduces noise in uniform image regions while maintaining and highlighting edges.

$$\frac{\partial I_t}{\partial t} = \nabla \cdot (c(|\nabla I_t|)\nabla I_t)$$

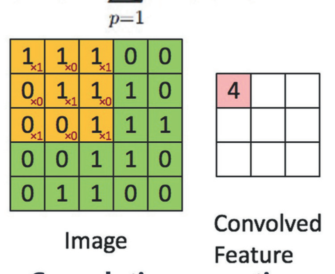
Gupta et al. (2022)

2. Convolutional Neural Networks (CNNs):

CNNs are powerful tools for extracting hierarchical features from images to perform tasks like image recognition. Kernels (or filters) slide along the input image and calculate feature maps using the convolution operation: Kose, U., et al. (2021)

$$\text{Feature Map}(i,j) = \sum_{p=1}^{k} W(p) \cdot (\text{Pixel Value})_p + b$$

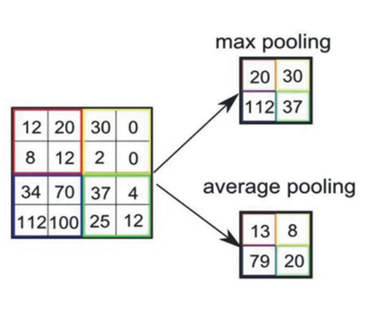
Using a kernel modifies the output dimensions due to the "edge effect" .



Convolution operation

Padding is introduced to fix this problem, preserving spatial dimensions

Pooling Operation:



Comparison of pooling

Forward Propagation:

Input data passes through convolutional layers, activation functions, and pooling to extract hierarchical features. Feature maps are flattened and passed into fully connected layers for classification.

The computation at each layer L can be expressed as:

$$Z^{[L]} = W^{[L]} \cdot A^{[L-1]} + b^{[L]}$$

$$A^{[L]} = g(Z^{[L]})$$

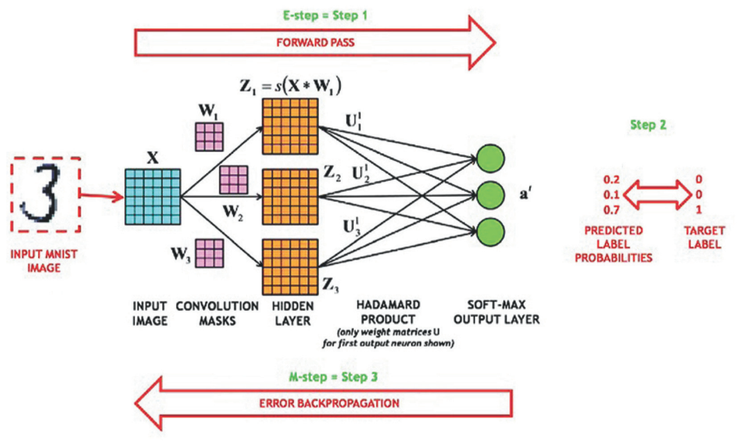
Backward Propagation:

Loss between the predicted output and the actual label is computed using a loss function like categorical cross-entropy. Gradients are calculated using backpropagation:

$$\frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial a_i} \cdot \frac{\partial a_i}{\partial Z} \cdot \frac{\partial Z}{\partial W_{ij}}$$

Weights are updated using gradient descent:

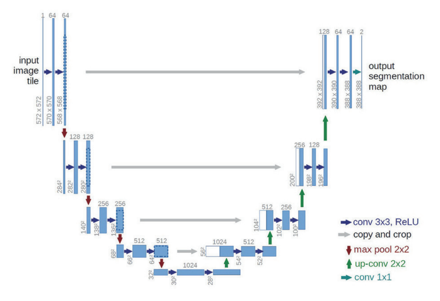
$$W_{\text{new}} = W_{\text{old}} - \alpha \cdot \frac{\partial E}{\partial W}$$



CNN architecture and process

3.U-Net for Binary Segmentation:

The U-Net architecture, with its encoder-decoder structure and skip connections, was implemented for binary segmentation of spinal cords from grayscale images, enabling precise pixel-level segmentation of anatomical features



U-Net architecture for image segmentation

Line Segmentation Using U-Net:

1.Input: Grayscale images (256×256×1), normalized to [0, 1] and padding to make the aspect ratio 1:1.

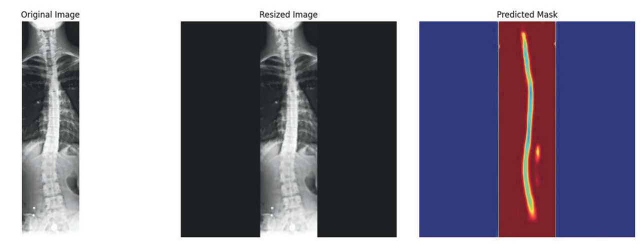
2.Encoding Path: Convolutional (3x3, ReLU) and max-pooling (2x2) layers with dropout to prevent overfitting.

3.Bottleneck: Two 3x3 convolutional layers (1024 filters, ReLU) with dropout.

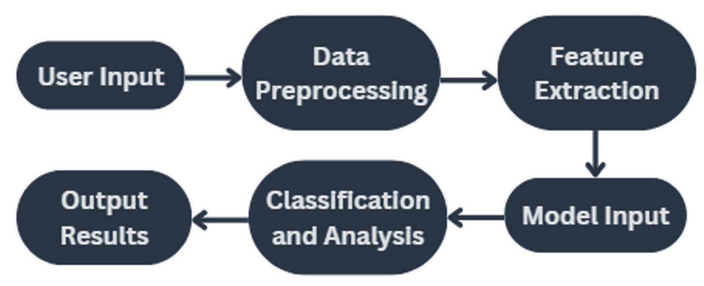
4.Decoding Path: Upsampling (2x2) with skip connections to retain spatial details.

5.Output Layer: 1x1 convolution with sigmoid activation for binary segmentation.

6.Training: Binary cross-entropy loss, Adam optimizer, and backpropagation for loss minimization.



Experimental Work



Dataset Overview:

The dataset consists of grayscale 25×50 pixels spinal X-ray images includes over 580 normal scans and 580 scoliosis scans. Contributions from Egyptian clinics, such as ***ARC for Scoliosis Physiotherapy (Dr. Mahmoud Ibrahim, PhD, PT), ScolioCare (Dr. Sarah M. Ali, MSc, PT), Dr. Tayseer Saber Abdeldayem, and 4Kids Therapy Clinic (Dr. Sarah M. Ali, MSc, PT)***, provided real-world data. Additionally, open datasets, including ***the Mendeley Dataset and Roboflow Universe.***

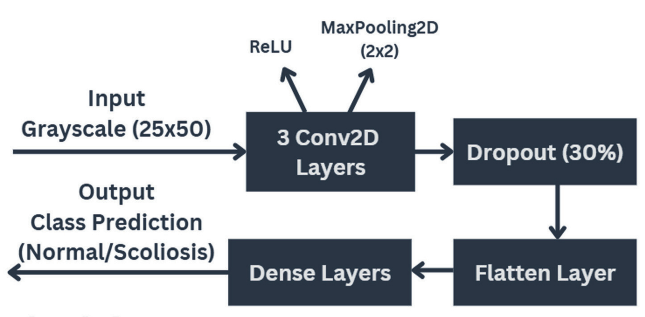
Data Preprocessing:

1.Grayscale Conversion: Images were converted to grayscale for consistency across color formats.

2.Resizing: Images were resized to 25×50 pixels.

3.Normalization: Pixel values were scaled to [0, 1] to stabilize training and enhance convergence.

Classification Model Architecture:

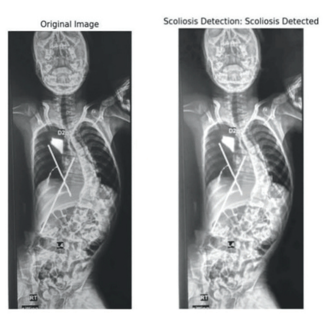


Training Methodology:

1.Dataset Splitting: 80% for training and validation, 20% for testing.

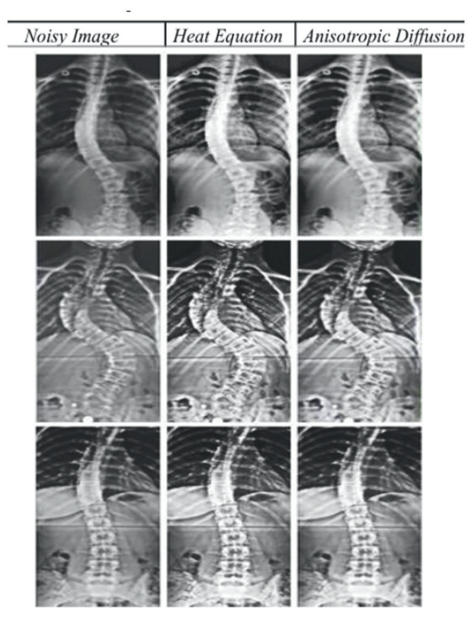
2.Hyperparameters: Batch size = 50, epochs = 20, Adam optimizer, and sparse categorical crossentropy as the loss function.

3.Evaluation: Accuracy was used as the primary performance metric.



Results

Overall Comparison:



Structural Similarity Index (SSIM):

Purpose: Measures similarity between original and processed images.

Interpretation: Higher scores indicate better preservation of the original image structure.

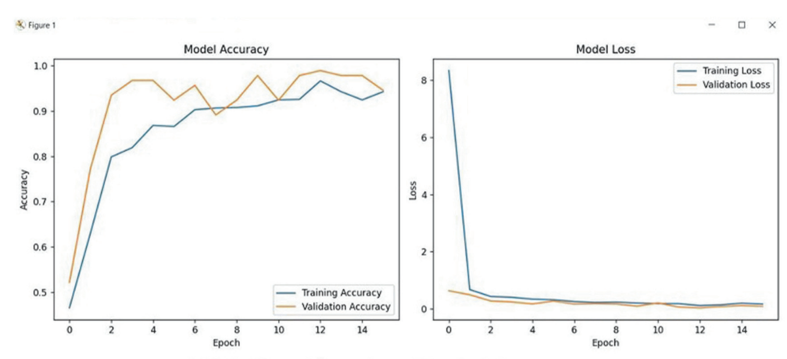
Bakurov, I., et al. (2022)..

$$SSIM(I_o, I_r) = \frac{(2\mu_x\mu_y + \alpha)(2\,\text{cov}(I_o, I_r) + \beta)}{(\mu_x^2 + \mu_y^2 + \alpha)(\sigma_x^2 + \sigma_y^2 + \beta)}$$

The SSIM scores were **0.9135** for the heat equation and **0.8219** for anisotropic diffusion, indicating that the heat equation achieved better structural similarity and retained more image quality compared to anisotropic diffusion.

Results of CNN Classification Model:

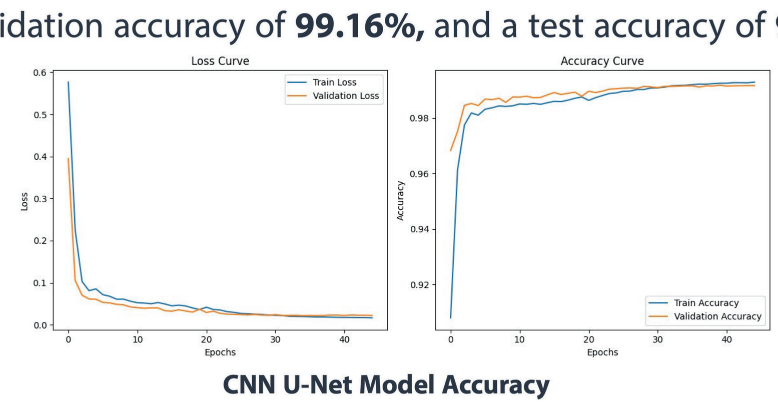
Our model was trained for 20 epochs, achieving a training accuracy of **96.64%**, a validation accuracy of **98.91%,** and a test accuracy of **84.58%.**



CNN Classification Model Accuracy

Results of Line Segmentation Using U-Net:

Our model was trained for 45 epochs, achieving a training accuracy of **99.3%**, a validation accuracy of **99.16%**, and a test accuracy of **98.74%.**



CNN U-Net Model Accuracy

Conclusion

This study compared the heat equation and anisotropic diffusion for preprocessing spinal X-ray images. The heat equation achieved higher SSIM scores for low-noise images, while anisotropic diffusion performed better on noisy, complex images. Combining preprocessing with a CNN achieved high scoliosis detection accuracy.

Future Work

Future improvements in preprocessing methods, CNN architecture, and dataset diversity could further enhance results. U-Net integration for spinal cord segmentation shows promise for accurate Cobb angle measurement, improving scoliosis monitoring and treatment. Future work will focus on automating and refining Cobb angle assessments to aid clinical decision-making.

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Scan For Refences