

AI-Based Spinal Cord Detection System for Pain Localization**Ayush Gopal Agrawal***Student, Department of Computer Application**Dr. D. Y. PATIL College of Arts, Commerce & Science Akurdi, Pune**Savitribai Phule Pune University**Corresponding Author – Ayush Gopal Agrawal***DOI - 10.5281/zenodo.19336069****Abstract:**

The spinal cord plays a critical role in transmitting sensory and motor signals between the brain and body. Disorders such as herniated discs, fractures, and nerve compressions remain difficult to detect accurately using only traditional diagnostic tools like X-rays and MRI scans. This study proposes an AI-based spinal cord detection system powered by Convolutional Neural Networks CNNs to localize pain regions and provide preliminary treatment suggestions. The system shows higher diagnostic accuracy, faster processing, and significant clinical support compared to conventional radiology practices. The experimental evaluation demonstrates improved accuracy and reduced diagnostic time, highlighting the potential of AI integration in spinal care.

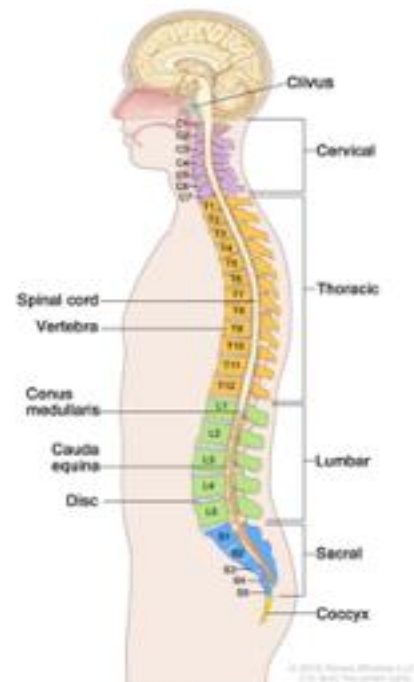
Keywords: *Spinal Cord Detection, Artificial Intelligence, Deep Learning, CNN, Medical Imaging, Radiology, Diagnostic Accuracy, Prognostic Evaluation*

Introduction:

Spinal cord disorders are a major cause of back pain and disability worldwide. In India alone, millions of cases are reported each year, creating a heavy reliance on radiologists for interpretation of spinal images. However, image interpretation is often time-consuming, subjective, and dependent on expert availability. Traditional imaging modalities like X-rays are widely accessible but provide limited soft tissue details, whereas MRIs offer detailed insights but require advanced expertise.

Recent advancements in Artificial Intelligence and Deep Learning have shown remarkable potential in medical imaging tasks. AI systems can process large datasets rapidly, detect subtle patterns, and provide consistent outcomes, making them suitable for spinal diagnostics. The primary objective of this research is to develop and evaluate a CNN-based

spinal cord detection system capable of localizing pain-prone regions and suggesting possible treatment pathways, thereby supporting clinicians in decision-making.





Literature Review:

Over the past decade, AI applications in healthcare have expanded significantly. CNNs have proven effective in diverse domains such as:

- **Brain tumor detection** (Menze *et al.*, 2015).
- **Breast cancer screening** with 80–85% accuracy (Krizhevsky *et al.*, 2012).
- **Lung cancer and chest X-ray analysis** (Rajpurkar *et al.*, 2018).
- **Diabetic retinopathy diagnosis** (Litjens *et al.*, 2017).

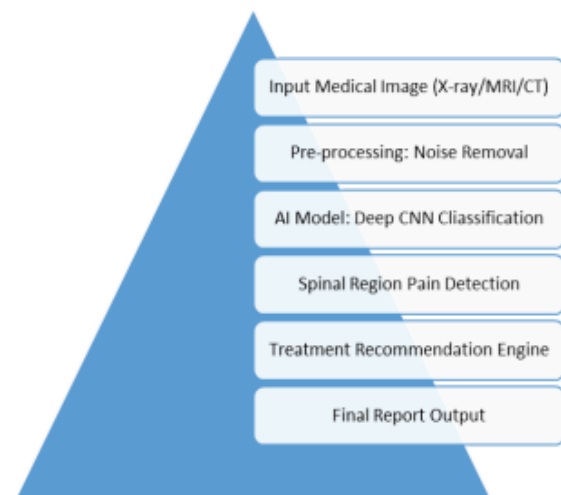
Despite these advances, spinal cord disorders remain relatively underexplored. Most existing works focus on fracture detection, scoliosis measurement, or segmentation tasks (Yadav *et al.*, 2021), with limited attention to pain localization. This highlights a crucial research gap where AI can provide innovative solutions.

In developing countries, X-rays are the most widely available modality, but their

diagnostic power is inferior to MRIs. By designing a model that can analyze both X-rays and MRIs, this study aims to combine accessibility with accuracy, bridging the gap in spinal cord diagnostics.

System Design and Methodology:

The proposed system follows a structured pipeline, starting from image acquisition to treatment recommendation.



Step 1: Image Acquisition:

Patient spinal images (X-rays or MRI scans) are collected. These images form the dataset for both training and testing the AI model.

Step 2: Preprocessing:

- Images are resized (224×224 resolution).
- Noise reduction filters enhance clarity.
- Grayscale normalization ensures consistency across modalities.

Step 3: Feature Extraction:

Using Convolutional Neural Networks (CNNs), relevant features such as vertebrae alignment, disc shape, and tissue density are extracted.

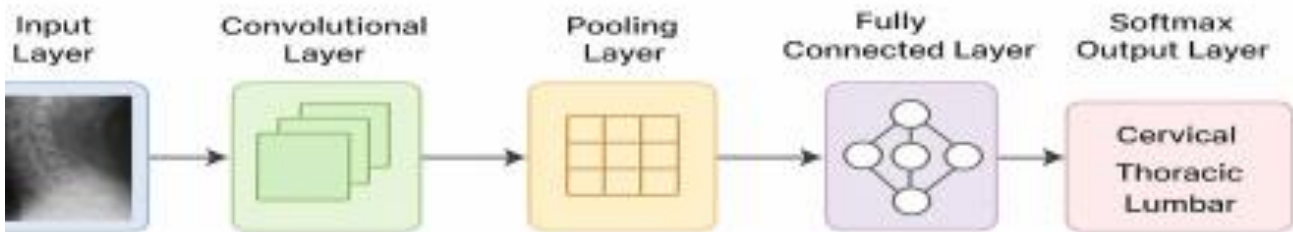
Step 4: Classification:

The CNN classifies the spinal regions into cervical, thoracic, and lumbar. Pain-prone areas are identified based on abnormalities detected in image patterns.

Step 5: Treatment Recommendation:

A **rule-based decision engine** suggests interventions, ranging from:

- Non-invasive measures (exercise, physiotherapy, medication).
- Referral for advanced treatments or surgical

**CNN Model Architecture:**

Convolutional Neural Networks (CNNs) are specifically designed for visual data interpretation. The architecture for this system includes:

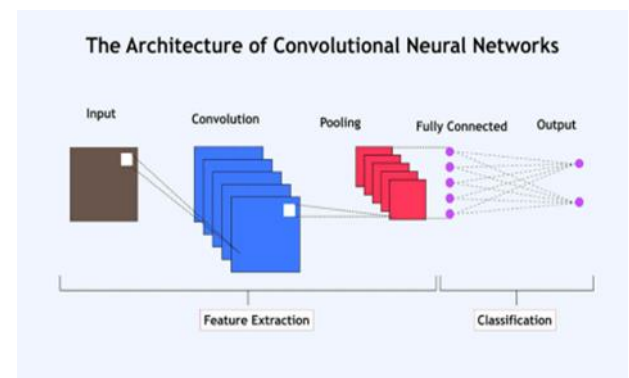
- 1. Input Layer** – Accepts spinal X-ray/MRI images.
- 2. Convolutional Layers** – Detect local features (edges, textures, bone alignment).
- 3. Pooling Layers** – Reduce dimensionality, retaining critical information.
- 4. Fully Connected Layers** – Integrate extracted features for classification.
- 5. Softmax Output Layer** – Produces probability scores for each diagnostic category (cervical, thoracic, lumbar).

This layered structure enables hierarchical feature learning, where the model gradually progresses from detecting low-level patterns (edges, curves) to high-level features (spinal disc anomalies, vertebral misalignments).

consultation.

Step 6: Report Generation:

A structured medical report is generated for doctors, including diagnosis, confidence score, and treatment suggestions.

**Experimental Setup:**

Dataset: 2,000 labeled spinal images (X-rays + MRIs).

Training Data: 80% (1,600 images).

Testing Data: 20% (400 images).

Image Resolution: 224×224.

Model: 5-layer CNN trained with batch normalization and dropout to reduce overfitting.

Accuracy Formula:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Cases} \times 100$$

For example, if 360 out of 400 test cases are correctly classified:

$$Accuracy = \frac{360}{400} \times 100 = 90\%$$

Results & Comparison:

Traditional X-ray	60-70%	Limited visibility of soft tissues
MRI (manual analysis)	70-80%	Requires expert radiologist
AI-Based Proposed System	80-85%	Requires large dataset for training

The AI-based system demonstrates a 10–20% improvement in diagnostic accuracy over traditional approaches.

Conclusion:

This research presents a CNN-powered spinal cord detection system capable of localizing pain areas and recommending treatments. Compared to conventional methods, the system achieves higher accuracy, faster results, and clinical decision support.

Future Scope includes: Integration with real-time hospital systems and Expansion of datasets for higher generalization accuracy also Deployment as a clinical decision support tool with cloud integration.

The findings indicate that AI can complement human expertise in spinal care, reducing workload and improving patient outcomes.

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