

A Comparative Survey of Deep Learning Techniques for Spine X-Ray Condition Classification

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Abstract: Spine-related disorders are common musculoskeletal conditions that can significantly affect mobility, posture, and quality of life. Spine X-ray imaging is widely used for the diagnosis and assessment of abnormalities such as scoliosis, spondylolisthesis, vertebral fractures, and degenerative changes. However, manual interpretation of radiographic images can be time-consuming and may be influenced by the experience of the radiologist. Recent advances in deep learning have provided effective approaches for automated analysis and classification of spine X-ray images. This paper presents a comparative survey of deep learning techniques used for spine X-ray condition classification. Various convolutional neural network (CNN) architectures and transfer-learning models, including ResNet, DenseNet, EfficientNet, and other advanced architectures, are reviewed based on their classification performance and applicability to different spinal conditions. The comparison considers important evaluation measures such as accuracy, precision, recall, F1-score, sensitivity, specificity, and area under the curve (AUC), along with dataset characteristics and computational requirements. The survey also discusses the advantages and limitations of existing approaches, including class imbalance, limited dataset diversity, lack of external validation, and challenges in model interpretability. Furthermore, emerging approaches such as attention mechanisms and transformer-based architectures are examined for their potential to improve automated spinal abnormality classification. The findings indicate that deep learning has considerable potential for assisting clinical decision-making and reducing the workload associated with manual spine X-ray interpretation. Finally, the study identifies current research gaps and future directions toward robust, explainable, and clinically deployable automated spine X-ray classification systems.

Keywords: Spine X-Ray, Deep Learning, Condition Classification, Convolutional Neural Network (CNN), Transfer Learning

I. INTRODUCTION

Spinal disorders are among the major musculoskeletal conditions affecting people across different age groups and can lead to pain, restricted movement, posture abnormalities, and reduced quality of life. Accurate and timely identification of spinal abnormalities is therefore important for appropriate clinical assessment and treatment planning. Spine X-ray imaging is

one of the most commonly used and accessible imaging modalities for evaluating the structural condition of the vertebral column. It provides useful information about spinal alignment, vertebral morphology, fractures, degenerative changes, scoliosis, and spondylolisthesis. However, the interpretation of spine X-ray images generally depends on the expertise and experience of radiologists, and manual assessment can become challenging when large numbers of images need to be examined [1, 2].

The rapid development of artificial intelligence (AI) and deep learning (DL) has created new opportunities for automated medical image analysis. Deep learning models can automatically learn complex visual patterns and discriminative features directly from medical images, reducing the dependency on manually engineered features. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification, object detection, and medical image analysis. Models such as ResNet, DenseNet, EfficientNet, and other transfer-learning architectures have been increasingly investigated for detecting and classifying spinal abnormalities from radiographic images. These approaches can potentially support clinicians by providing automated and consistent predictions [3, 4].

Different spine X-ray studies have focused on different clinical conditions and classification tasks. For example, deep learning has been applied to the identification of scoliosis, spondylolisthesis, vertebral fractures, spinal curvature abnormalities, and lumbar degenerative changes. Some studies have employed conventional CNN architectures, whereas others have used transfer learning to overcome the limitations of relatively small medical datasets [5]. More recent approaches have also incorporated attention mechanisms and transformer-based architectures to improve feature representation and classification performance. Although these studies demonstrate promising results, their reported performance cannot always be directly compared because of differences in datasets, image quality, patient populations, number of classes, preprocessing techniques, and evaluation criteria [6, 7].

A comparative assessment of existing deep learning techniques is therefore necessary to understand their relative strengths, limitations, and suitability for spine X-ray condition classification. A survey can provide a systematic overview of the models used, the spinal conditions addressed, datasets employed, evaluation metrics, and reported outcomes. It can also identify important challenges such as class imbalance, limited and heterogeneous datasets, overfitting, lack of external validation, variations in radiographic views, and limited model interpretability. These factors are particularly important when considering the transition of deep learning models from experimental research to practical clinical applications [8].

This paper presents a comparative survey of deep learning techniques for spine X-ray condition classification. The study reviews existing research based on deep learning architecture, classification objective, dataset characteristics, preprocessing methods, and evaluation measures such as accuracy, precision, recall, F1-score, sensitivity, specificity, and AUC. The comparative analysis further examines the applicability of different architectures to various spinal conditions and highlights the emerging role of transfer learning, attention-based networks, and transformer models. Finally, the study discusses existing research gaps and

future directions for developing robust, explainable, generalizable, and clinically deployable spine X-ray classification systems.

II. LITERATURE REVIEW

Maddu et al. [1], study focused on identifying osteoporosis-related abnormalities from radiographic images and demonstrated the potential of deep learning for automated bone-health assessment. Deep learning models can learn discriminative radiographic features that may be difficult to identify consistently through conventional image-processing approaches. The study highlights the usefulness of automated X-ray analysis for supporting early osteoporosis screening and reducing dependence on manual interpretation. However, the effectiveness of such models may depend on the size, quality, and diversity of the available X-ray dataset. This work is relevant to the present survey because osteoporosis represents an important spine-related condition that can be addressed through automated deep learning-based classification. Yametkar et al. [2] presented a multi-class spine X-ray condition classification approach for automatically identifying different spinal conditions from X-ray images. Unlike binary classification systems that distinguish only between normal and abnormal cases, the study considered multiple conditions, making the classification task more challenging and clinically relevant. The work demonstrates the applicability of machine learning/deep learning techniques for extracting relevant features from spine radiographs and assigning images to different disease categories. Multi-class classification can provide more detailed diagnostic information and may assist clinicians in preliminary assessment. However, differences in the number of classes, dataset distribution, and image characteristics can influence model performance. The study provides a strong foundation for comparative analysis of multi-condition spine X-ray classification methods.

Degadwala et al. [3] proposed DeepSpine, a deep learning-based framework for multi-class classification of spine X-ray conditions. The study focused on using deep neural networks to automatically learn relevant features from spinal radiographs and classify different conditions. The use of deep learning reduces the requirement for manually designed features and allows the model to capture complex patterns associated with spinal abnormalities. The multi-class nature of the proposed system makes it more suitable for real-world diagnostic scenarios than a simple normal/abnormal classifier. Nevertheless, the generalization of the model to larger and more diverse datasets remains an important consideration. This work is particularly relevant to the present survey because it directly addresses multi-class spine X-ray condition classification using deep learning.

Sisodia et al. [4] investigated spine disease detection in spinal X-ray images using machine learning techniques. The study explored the use of computational methods for identifying spinal diseases from radiographic images, demonstrating the potential of automated systems to support the diagnosis process. Machine learning-based analysis can extract image characteristics and distinguish between different disease patterns, thereby reducing the effort required for manual image examination. The study also indicates that appropriate preprocessing and feature extraction are important for achieving reliable classification results.

However, traditional machine learning methods generally depend more heavily on feature engineering than modern deep learning architectures. Therefore, this work provides a useful baseline for understanding the transition from conventional machine learning to automated deep feature learning in spine X-ray analysis.

Singh et al. [5] study focused on automatically analyzing vertebral structures and identifying abnormalities using AI techniques. Automated vertebral diagnosis is important because accurate identification of vertebral regions provides the foundation for subsequent disease classification and quantitative assessment. The study demonstrates how artificial intelligence can reduce the dependence on manual vertebral examination and potentially improve the efficiency of radiographic analysis. However, vertebral localization and diagnosis can be affected by overlapping anatomical structures, variations in patient positioning, and differences in image quality. The study therefore contributes to the development of AI-assisted systems for automated spine X-ray interpretation.

Saechueng et al. [6] method builds upon the Histogram of Oriented Gradients (HOG) feature descriptor by assigning appropriate weights to extracted features to improve the representation of relevant structural information. Spondylolisthesis classification requires the identification of subtle changes in vertebral alignment, making effective feature extraction important. The study demonstrates that carefully designed handcrafted features can provide useful classification performance even without complex deep neural networks. However, handcrafted feature-based methods may have limited adaptability when image characteristics and disease patterns vary significantly. This study provides an important comparison point between classical image-processing approaches and deep learning-based spine classification.

Xuan et al. [7] study employed transfer learning to utilize knowledge learned from large-scale image datasets for medical image-based spinal disease diagnosis. Transfer learning is particularly useful when medical datasets are relatively small because training a deep network entirely from scratch can lead to overfitting. The findings demonstrate the potential of pretrained deep learning architectures for automated spinal disease analysis. However, the study is based on MRI rather than X-ray images, and therefore its findings cannot be directly generalized to radiographic spine classification. Nevertheless, it provides valuable methodological insight into the use of transfer learning for automated spinal disease diagnosis. Bakaev et al. [8] investigated focused on segmentation of spinal structures, which is an important preprocessing step for automated vertebral recognition and disease analysis. Accurate segmentation can isolate relevant anatomical regions and reduce the influence of irrelevant image information. Such approaches can subsequently support vertebra-level classification, localization, and abnormality detection. However, segmentation of vertebrae in X-ray images is challenging because of overlapping bones, varying contrast, and anatomical complexity. This work is therefore significant for the present survey because effective segmentation and localization can improve the reliability of downstream deep learning-based spine condition classification.

Tavana et al. [9] presented a comparative study on spinal curvature classification using radiography images, evaluating deep learning methods against classical machine learning

approaches. The study examined the capability of automated algorithms to distinguish different types of spinal curvature from radiographic images. Deep learning methods provide an advantage by automatically learning hierarchical image representations, whereas classical approaches generally require manually engineered features. The comparison demonstrates the growing importance of deep learning for radiographic spine analysis and provides evidence regarding its potential advantages over conventional approaches. However, performance differences can depend on dataset size, preprocessing procedures, feature representations, and selected classification algorithms. This study is highly relevant to the present survey because it directly compares deep learning and classical techniques for spine radiograph classification. Jang et al. [10] investigated demonstrated the application of deep learning to identify clinically important vertebral abnormalities from lateral spine radiographs. Automated detection of vertebral fractures and osteoporosis can support early screening and assist clinicians in identifying patients who may require further assessment. The use of deep learning allows the system to learn complex radiographic patterns associated with vertebral structural changes without relying entirely on manually designed features. The study highlights the clinical potential of AI-assisted spine X-ray interpretation; however, further validation across different populations, imaging systems, and clinical settings is necessary before widespread deployment. This work strengthens the evidence supporting deep learning as a promising approach for automated spine X-ray condition classification.

III. SPINE X-RAY

A Spine X-ray is a radiographic imaging technique used to examine the bony structures of the vertebral column. It uses X-rays to produce images in which dense structures such as the vertebrae appear relatively white, while less-dense tissues appear darker. Spine X-rays can be obtained for different regions, including the cervical, thoracic, lumbar, sacral, and coccygeal regions [11, 12].

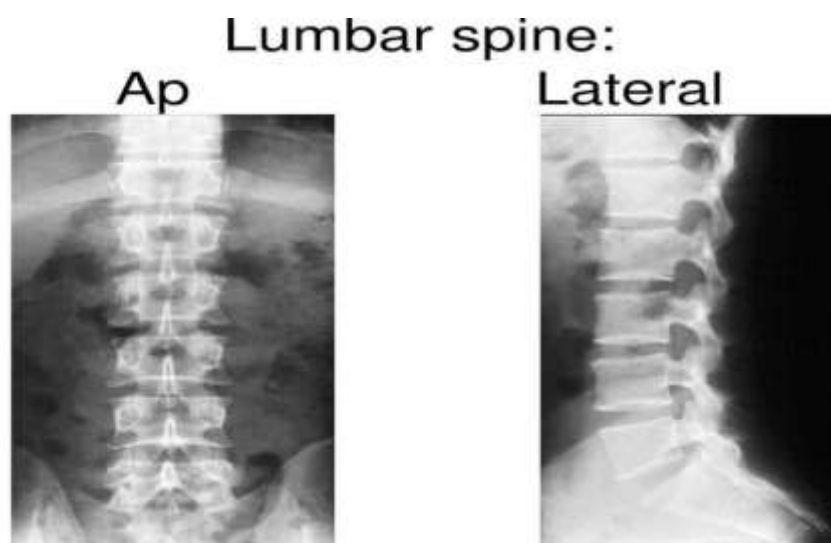


Figure 1: Spine X-ray

The vertebral column consists of different anatomical regions: 7 cervical vertebrae (C1–C7), 12 thoracic vertebrae (T1–T12), and 5 lumbar vertebrae (L1–L5), followed by the sacrum and coccyx. Intervertebral discs are located between adjacent vertebrae and help provide cushioning and flexibility.

In clinical practice, spine X-rays are commonly used to evaluate spinal alignment, vertebral structure, fractures, abnormal curvature, degenerative changes, osteoporosis-related abnormalities, and conditions such as scoliosis and spondylolisthesis. Different views, particularly anteroposterior (AP) and lateral views, provide complementary information about vertebral alignment and structure.

For deep learning-based spine X-ray condition classification, these radiographic images are used as input data. A deep learning model can learn characteristic visual patterns from X-ray images and classify them into predefined categories such as Normal, Scoliosis, Spondylolisthesis, Osteoporosis, Vertebral Fracture, or other spinal conditions. Thus, automated X-ray classification can assist in screening and provide decision-support information to clinicians, although it is intended as an aid rather than a replacement for professional diagnosis.

Table 1: Spine Condition

Class	Spine Condition	Description
1	Normal	Normal vertebral alignment and structure
2	Scoliosis	Abnormal lateral curvature of the spine
3	Spondylolisthesis	Forward or backward displacement of one vertebra relative to another
4	Osteoporosis	Reduced bone density that can increase vertebral fracture risk
5	Vertebral Fracture	Structural break or collapse of a vertebra
6	Degenerative Changes	Structural changes associated with spinal degeneration

IV. DEEP LEARNING

Deep Learning (DL) is a subfield of Artificial Intelligence (AI) and Machine Learning that uses multi-layered artificial neural networks to automatically learn complex patterns and representations from large amounts of data. Unlike traditional machine learning, where features often need to be manually extracted, deep learning models can learn relevant features directly from raw images, text, audio, or other data.

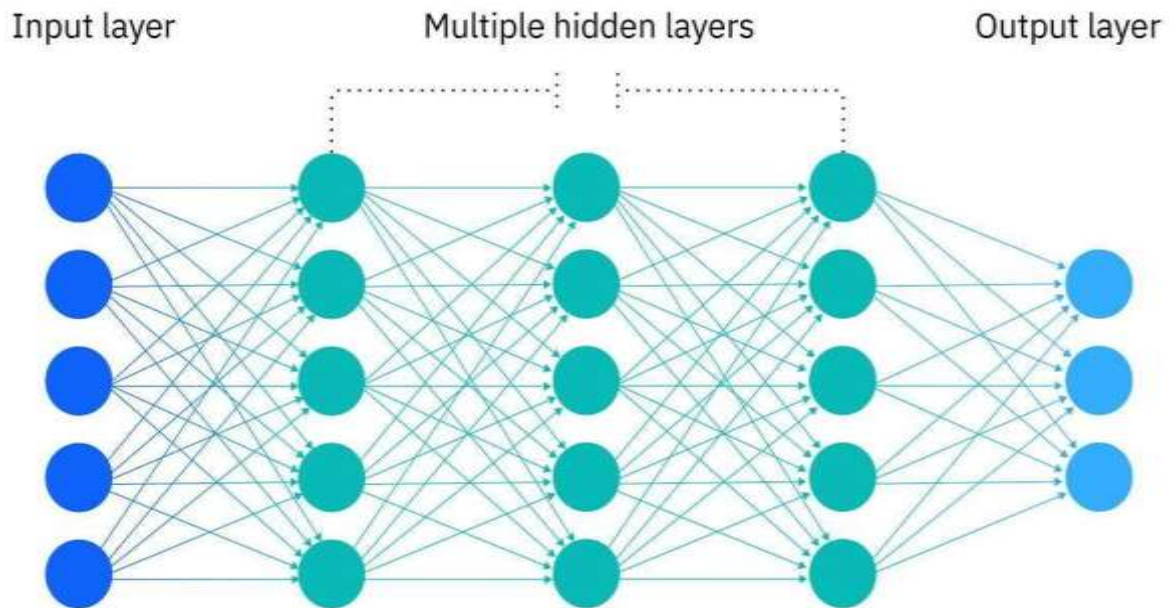


Figure 2: Deep learning

For Spine X-Ray Condition Classification, deep learning is particularly useful because X-ray images contain complex anatomical structures and subtle abnormalities. A deep learning model can learn these patterns and classify an X-ray into predefined categories such as Normal, Scoliosis, Spondylolisthesis, Osteoporosis, Vertebral Fracture, or Degenerative Changes.

Deep Learning Process for Spine X-Ray Classification

Input X-Ray → Preprocessing → Feature Extraction → Classification → Predicted Condition

1. Input: Spine X-ray images are provided to the model.
2. Preprocessing: Images are resized, normalized, and, when required, enhanced to improve image quality.
3. Feature Extraction: CNN layers automatically learn features such as vertebral shape, alignment, edges, and structural abnormalities.
4. Classification: Fully connected or classification layers use the extracted features to determine the condition.
5. Output: The model provides the predicted class, often along with a probability/confidence score.

Common deep learning architectures used for medical image classification include CNN, ResNet, DenseNet, EfficientNet, Inception, MobileNet, and Transformer-based models. Transfer learning is also widely used because medical datasets are often relatively limited.

V. CONCLUSION

This comparative survey reviewed the application of deep learning techniques for Spine X-ray Condition Classification and examined their potential for automated identification of various spinal abnormalities. The reviewed studies demonstrate that deep learning, particularly CNN-based and transfer-learning architectures such as ResNet, DenseNet, and EfficientNet, can

effectively learn discriminative features from spine X-ray images and achieve promising classification performance. These approaches have been applied to conditions including scoliosis, spondylolisthesis, osteoporosis, vertebral fractures, and spinal degenerative abnormalities. Compared with conventional machine learning methods that rely on handcrafted features, deep learning provides automated feature extraction and better adaptability to complex radiographic patterns.

However, the comparative analysis also reveals several challenges, including limited and imbalanced datasets, variations in image quality and radiographic views, differences in classification categories, lack of standardized evaluation protocols, limited external validation, and insufficient model interpretability. These factors make direct comparison between existing studies difficult and can affect the generalization of trained models to different clinical environments. Future research should therefore focus on developing larger and more diverse datasets, standardized benchmarking protocols, explainable AI techniques, multi-condition classification frameworks, and lightweight models suitable for clinical deployment. Overall, deep learning has significant potential to support automated, accurate, and efficient spine X-ray analysis, while further clinical validation is required for reliable real-world adoption.

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