A Comprehensive Survey on Deep Learning Methods for Automated Spinal Fracture Detection and Classification

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***Abstract*—Trauma, osteoporosis, or metastatic diseases are the most prevalent causes of spinal fractures, a dangerous medical condition. These fractures have the potential to cause serious neurological problems, if they are misdiagnosed or misclassified, leading to diminished quality of life and persistent pain. Conventional diagnostic methods, including X-rays, computed tomography (CT), and magnetic resonance imaging (MRI), rely on expert interpretation by radiologists. However, manual assessment is time-consuming, subject to inter-observer variability, and may lead to diagnostic inconsistencies, particularly in subtle or complex cases. With advancements in artificial intelligence (AI), deep learning has revealed abundant possibility in automating spinal fracture detection and classification, improving both speed and accuracy. In recent years, deep learning techniques have developed as a dominant tool for automated spinal fracture detection and classification, offering great precision and effectiveness. This survey delivers a broad review of state-of-the-art deep learning models applied to spinal fracture analysis, covering CNNs, transformer-based architectures, and hybrid approaches. We analyze several publicly accessible datasets, preprocessing techniques, model architectures, and evaluation metrics used in the literature. The research gap is examined in the outcome section of this study. Finally, we outline future research directions, emphasizing the need for improved generalization, explainability, and integration with clinical workflows. This survey aims to serve as a useful reference for researchers and clinicians seeking to advance automated spinal fracture diagnosis using deep learning.**

Keywords: Spinal fractures, Diagnosis, X-rays, Radiologists, Neurological problems.

I. Introduction

Spinal fractures are a significant medical concern, often resulting from trauma, osteoporosis, or metastatic diseases. If left undiagnosed or misclassified, these fractures can lead to severe neurological impairments, chronic pain, and reduced quality of life. Conventional diagnostic methods, including X-rays, computed tomography (CT), and magnetic resonance imaging (MRI), rely on expert interpretation by radiologists. However, manual assessment is time-consuming, subject to inter-observer variability, and may lead to diagnostic inconsistencies, particularly in subtle or complex cases. With advancements in artificial intelligence (AI), deep learning has revealed abundant possibility in automating spinal fracture detection and classification, improving both speed and accuracy. CNNs, Vision Transformers (ViTs), and hybrid models are utilized to analyze medical images, overtaking outdated machine learning approaches in feature extraction and classification. These AI driven methods aim to assist radiologists by enhancing diagnostic reliability and enabling real-time automated analysis. This survey offers a comprehensive analysis of recent advancements in deep learning-based spinal fracture detection and classification. The second section explores existing evaluation techniques, highlighting the accuracy obtained using different approaches. The final section summarizes the main outcomes and, discusses ongoing challenges, and outlines future research directions to improve AI-driven spinal fracture diagnosis.

II. Literature Survey

Spinal fracture detection is studied using many approaches.

[1] Proposes a deep-learning model based on Channel and Spatial Attention to improve cervical spine fracture detection using CT images. The model, utilizing CNN architecture with attention mechanisms, achieved accuracy of 99.50%.

[2] Explores the use of machine learning and deep learning in spinal injury diagnosis and prognosis, analyzing 39 studies focused on diagnostic tasks such as vertebral fracture detection and classification using deep learning, and 5 on prognosis, predicting outcomes like vertebral collapse and future fractures. The study underlines the efficacy of CNNs and other AI models in medical imaging, emphasizing challenges like data availability, model interpretability, and clinical integration, while also outlining future research directions to enhance predictive accuracy and practical usability. [3] Introduces DeepSpine, a deep learning model designed for multi-class classification of spine conditions from X-ray images. Using Convolutional Neural Networks (CNNs) and transfer learning, the model effectively identifies abnormalities such as Scoliosis, Osteochondrosis, Osteoporosis, Spondylolisthesis, and Vertebral Compression Fractures (VCFs). Trained on a Kaggle dataset, DeepSpine demonstrates 99% accuracy, outperforming VggNet16 and ResNet50, highlighting its potential automated spine condition diagnosis in musculoskeletal radiology.

[4] Explores the use of different models, for cervical spine fracture detection. The proposed model uses a dataset of 2,009 annotated cervical spine images and achieves high accuracy by utilizing transfer learning with VGG16 and ResNet50V2. The

findings highlight the potential of AI-driven systems to enhance early diagnosis, reduce diagnostic errors, and assist radiologists in medical imaging analysis. [5] Explores machine learning techniques, particularly CNNs, for automated bone fracture detection from X-ray images. The model was uses a large dataset of annotated X-ray images, employing data augmentation and preprocessing techniques to enhance accuracy. The results demonstrate the CNN-based model's effectiveness in detecting fractures, reducing diagnostic errors, and assisting radiologists in faster and more precise medical image analysis. [6] Proposes a two-stage deep learning approach for CT scan images for the detection of fracture. The first stage employs a Convolutional Neural Network (CNN) for binary fracture classification, while the second stage utilizes YOLOv5 and YOLOv8 models to detect and classify fractures in seven cervical vertebrae. The model achieves high precision (0.900), recall (0.890), and mAP50 (0.935), demonstrating the efficacy of deep learning in automating fracture diagnosis and assisting radiologists with improved accuracy and speed. [7] Proposes a deep learning-based model for automated cervical spine fracture detection using CT scan images. The model applies Computer Aided Diagnosis (CAD) and advanced Convolutional Neural Networks (CNNs) to enhance early detection and classification of vertebral fractures. The research demonstrates that automating cervical spine fracture diagnosis can significantly reduce interpretation time, improve diagnostic accuracy, and assist radiologists in resource-limited healthcare settings. [8] Explores the use of deep learning-based object detection, specifically YOLOv3 (You Only Look Once v3), for automated rib fracture detection in chest radiographs. The model uses a multicenter quality normalized radiographs and achieved high sensitivity (91%) and accuracy (85.1%), outperforming junior radiologists and performing comparably to senior radiologists. The findings suggest that CNN-based AI models can enhance early rib fracture detection, reduce missed diagnoses, and assist radiologists by improving diagnostic efficiency. [9] Introduces VERTE-X, a deep learning-based model designed to detect vertebral fractures (VFs) and osteoporosis from lateral spine X-ray images. The model, using EfficientNet-B4 CNNs, was trained on a dataset of 26,299 X-rays from 9,276 patients, achieving an AUROC of 0.93 for VFs and 0.85 for osteoporosis. The results indicate that integrating AI-based detection with clinical indications can improve the referral of high-risk individuals for DXA testing, enhancing osteoporosis screening and fracture risk assessment. [10] Presents an AI-based classification system for cervical spine fractures and dislocations using AlexNet and GoogleNet. The model, trained on 2,009 X-ray images (530 dislocations, 772 fractures, 707 normal cases), achieved 99.55% accuracy, 99.33% sensitivity, and 99.67% F1-score. The study focuses on the use of transfer learning in medical imaging and tells that the system could be integrated into radiology workflows for real-time emergency diagnosis. [11] Proposes Vision Transformers (ViT) for cervical spine fracture detection using CT scans. Achieves 98% accuracy, leveraging cloud based resources for scalability. Highlights the explainability of AI models using attention-based heatmaps. [12] Uses CNNs with supervised and transfer learning for vertebral fracture detection. Employs image normalization and augmentation to enhance generalization. Shows high accuracy, improving diagnosis speed and reducing false negatives. [13] Develops a hybrid image thresholding technique combined with SVM classification. Uses watershed segmentation to detect spinal cord atrophy in MRI images. Achieves 0.9783 true positive rate and 0.9683 accuracy, outperforming traditional methods. [14]Implements a deep CNN model trained on 2,019 CT scans with 3D volume processing. Compares performance with radiologists, achieving comparable sensitivity and accuracy. Uses PyTorch for efficient training and real-time fracture detection. [15] Proposes a new method for detecting and localizing vertebral fractures (VFs) in plain frontal radiographs (PARs). The model, trained on 1,306 images, achieved 73.5% accuracy, 73.8% sensitivity, and an AUC of 0.72, signifying its possiblity for automated VF screening. Despite promising results, further improvements in clinical validation and model interpretability are needed for real-world deployment. [16] Proposes a deep learning- based segmentation model (MDR2-UNet) to automate vertebral segmentation and measure vertebral compression ratio (VCR) from X-ray images. The model, trained on 339 lateral thoracic and lumbar spine images, achieved 99.2% accuracy, 99.5% specificity, demonstrating high reliability. The findings suggest that AI- driven segmentation can enhance osteoporosis and fracture diagnosis, reducing manual workload for radiologists. [17] Proposes an improved Faster-RCNN model for automated spinal fracture detection in CT images, addressing challenges like low contrast and irregular vertebral shapes. By optimizing the Region Proposal Network (RPN) and anchor sizes, the model achieves a mean average precision (mAP) of 73.3% and a detection speed of 0.0381 seconds per image, making it appropriate for clinical real-time applications. The results recommend that deep learning can enhance exactness and efficacy in spinal lesion detection, reducing radiologists workload. [18] Proposes a deep learning-based system for automated Cobb angle measurement from frontal spine radiographs to assess scoliosis. The model, using a confidence map and vertebral-tilt field, achieves a 3.51° circular mean absolute error (CMAE) and 7.84% symmetric mean absolute percentage error (SMAPE), ensuring high accuracy and visual explainability. The method enhances clinician workflow by providing both Cobb angle estimates and vertebral structural insights, improving scoliosis diagnosis. [19] Evaluates an FDA-approved CNN by Aidoc for finding cervical spine fractures on CT scans, comparing its performance to radiologists. The CNN achieved 92% accuracy 76% sensitivity, and 97% specificity, performing slightly lower than radiologists (95% accuracy, 93% sensitivity, 96% specificity). While the CNN shows promise for work-list prioritization and assisting radiologists, improvements in sensitivity is required before clinical adoption. [20] Evaluates a CNN for detecting and classifying proximal humerus fractures from anteroposterior (AP) shoulder radiographs. The model achieved 96% accuracy, 1.00 AUC, and 0.99 sensitivity, outperforming general physicians and matching specialized shoulder orthopedists in complex fracture detection. The findings suggest deep learning can enhance orthopedic fracture diagnosis, reducing human errors and improving clinical efficiency.

TABLE I. SUMMARY OF DIFFERENT PAPERS

Author	Year	Techniques	Description
Abhishek Kumar Pandey, Kedarnath Senapati	2025	Wide ResNet-40, DenseNet-121, and EfficientNet-B7	The overall accuracy, specificity, sensitivity, and F1-score of the proposed model are 94.62%, 93.51%, 95.29%, and 93.16%, respectively
Vishesh Tanwar	2024	CNN, Attention Mechanisms	Achieved 99.50% accuracy, 99.50% precision, and 97.25% recall on 4,200 CT scans.
Satoshi Maki	2024	CNN, Random Forests, U-Net	CNN modelsachieved high accuracy in vertebral fracture detection, with some models reaching 90%+ sensitivity and specificity.
Sheshang Degadwala	2024	CNN, Transfer Learning	Kaggle-trained CNNs achieving 99% accuracy, outperforming VGG16 and ResNet50.
Mohamed Nadjib Meadi	2024	CNN, VGG16 & ResNet50V2	Achieved 99.55% accuracy, 99.76% recall, 100% Precision, and 99.57% F1-score.
Muhammad Yaseen	2024	CNN, YOLOv8 Object Detection	Achieved 97.8% accuracy, precision of 90.0%, recall of 89.0%, and mAP50 of 93.5%.
Paweł Chilad	2023	Vision Transformer, YOLOv5	Vision Transformers matched CNN-based models with 98% accuracy while improving explainability.
Pradeep S	2022	CNN, SVM Classifier	Achieved 96.83% accuracy in spinal cord injury classification with reduced false positives.
Hsuan-Yu Chen	2021	ResNeXt-50, Transfer Learning	Detected vertebral fractures from Radiographs with 73.59% accuracy.

III. OUTCOME OF THE RESEARCH

Current methods for spinal fracture detection using deep learning primarily rely on single-modality imaging, which may lack comprehensive anatomical and pathological details. While attention mechanisms have shown promise in medical imaging, their integration with multimodal data for spinal fracture detection remains under explored. There is a critical need for a deep learning model that effectively integrates multimodal imaging with attention mechanisms to enhance detection accuracy, improve feature interpretability, and ensure clinical applicability

IV. CONCLUSION

With CNNs, Vision Transformers, and object identification models reaching high accuracy and several methods further enhance precision, while segmentation models aid in osteoporosis and scoliosis assessment. Despite advancements, challenges like data limitations and clinical validation remain. In upcoming days it is required for improving sensitivity and real-world integration also obtaining the dataset which is useful for the research is also needed. AI driven diagnostics can assists radiologists which can reduce the errors.

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