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Spinexnet: An Intelligent Deep Learning Architecture For Multiclass Spinal Disorder Classification From Radiographic Images

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Abstract- Spinal disorders such as scoliosis, osteoporosis, spondylolisthesis, osteochondrosis, and vertebral compression fractures are major contributors to chronic back pain and physical disability worldwide. Early and precise diagnosis using spine X-ray imaging plays a crucial role in effective treatment planning and long-term patient care. However, manual analysis of radiographic images is time-consuming and highly dependent on the expertise of radiologists, which may lead to variability in diagnosis.To address this challenge, this study presents a deep learning-based multi-class classification framework for the automatic detection of various spinal conditions from X-ray images. The proposed system utilizes Convolutional Neural Networks (CNNs) for automated feature extraction and classification. Multiple pre-trained architectures, including VGGNet and ResNet, are evaluated and compared with a customized CNN model to identify the most effective approach. The dataset undergoes preprocessing steps such as resizing, normalization, and augmentation to improve model generalization and robustness.Experimental results demonstrate that the proposed CNN model achieves superior performance, with high accuracy, precision, recall, and F1-score across multiple spine condition categories. The system provides reliable and consistent predictions, highlighting its potential as a computer-aided diagnostic tool. By assisting medical professionals with faster and more standardized analysis, the proposed framework can contribute to improved clinical decision-making and better patient outcomes.

Keywords: Deep Learning, Convolutional Neural Network (CNN), Spine X-ray Classification, Multi-Class Classification, Medical Image Analysis, Transfer Learning, Computer-Aided Diagnosis (CAD), Radiographic Imaging.

I. INTRODUCTION

Cloud computing has emerged as a dominant Spinal disorders represent a significant global healthcare concern, affecting individuals across all age groups. Conditions such as scoliosis, osteoporosis, spondylolisthesis, osteochondrosis, and vertebral compression fractures often result in persistent pain, reduced mobility, and diminished quality of life. Early detection and accurate classification of these disorders are essential for appropriate medical intervention and long-term management [14].

Spine X-ray imaging remains one of the most commonly used diagnostic tools due to its affordability, accessibility, and effectiveness in visualizing bone structures. Despite its advantages, interpreting spine X-rays manually can be complex and time-intensive. Diagnostic accuracy depends heavily on the radiologist's expertise, and subtle abnormalities may sometimes go unnoticed, particularly in high-volume clinical settings. The increasing demand for radiological evaluations further emphasizes the need for automated and reliable diagnostic systems [2], [12], [15].

In recent years, deep learning—especially Convolutional Neural Networks (CNNs)—has significantly transformed medical image analysis. CNN models are capable of automatically learning hierarchical and spatial features directly from images, eliminating the need for manual feature engineering. Their ability to identify complex patterns makes them particularly suitable for multi-class classification tasks in radiographic imaging.

Several studies have demonstrated the effectiveness of deep learning approaches for detecting spinal abnormalities and analysing medical images such as X-rays, CT scans, and MRI scans [1], [3], [5], [9], [10], [11], [13].

Motivated by these advancements, this study proposes a deep learning-based multi-class classification framework for spine X-ray images. The objective is to automatically classify different spinal conditions into predefined categories, including both healthy and pathological cases. The proposed system integrates preprocessing techniques, normalization, and multiple CNN architectures to enhance performance and generalization capability [4], [6], [7], [8].

By incorporating artificial intelligence into radiographic analysis, this research aims to support clinicians in achieving faster, more consistent, and more accurate diagnoses. The study contributes to the growing field of computer-aided diagnosis by demonstrating the effectiveness of deep learning models in spine condition classification [1], [3], [10].

II. LITERATURESURVEY

The application of artificial intelligence and deep learning in spinal imaging has gained significant attention in recent years. Several studies have explored automated techniques to enhance diagnostic accuracy and efficiency in detecting spinal abnormalities. Earlier research focused on machine learning-based approaches for detecting vertebral abnormalities from X-ray and MRI images. Traditional feature extraction methods combined with classifiers such as Support Vector Machines (SVM) and Random Forests were used to identify specific spinal conditions [12], [13], [15].

While these methods showed promising results, they relied heavily on handcrafted features, limiting their ability to generalize across diverse datasets.

With the advancement of deep learning, researchers began applying Convolutional Neural Networks (CNNs) for spine image classification. Enhanced CNN architectures have been developed for lumbar spine disease detection, demonstrating improved accuracy compared to classical methods [3]. Comparative studies between deep learning models and traditional techniques have consistently shown that CNN-based approaches outperform conventional image processing algorithms in identifying spinal curvature types and degenerative conditions [4].

Transfer learning has also been widely adopted in spinal imaging research. Pre-trained models such as VGGNet, ResNet, and AlexNet have been fine-tuned for scoliosis detection, osteoporosis assessment, and vertebral compression fracture identification [6], [7], [8].

These approaches leverage previously learned image representations, improving performance even when training data is limited. Some studies have extended deep learning applications to MRI and CT imaging for spinal disease diagnosis and postoperative condition monitoring [5], [11]. Others have focused on automated classification systems for lumbar spine X-rays and severity assessment of spinal deformities [1], [9], [10].

Collectively, these contributions highlight the growing potential of deep learning in musculoskeletal radiology.

Despite these advancements, challenges remain in achieving robust multi-class classification across multiple spinal conditions within a single unified framework. Many existing systems focus on binary classification or specific diseases.

Therefore, there is a need for a comprehensive deep learning model capable of accurately distinguishing multiple spine conditions simultaneously.

The proposed work addresses this gap by developing and evaluating a multi-class CNN-based framework designed specifically for spine X-ray condition classification, ensuring improved accuracy, robustness, and clinical applicability [3], [4], [6].

III.SYSTEM ANALYSIS

A. Existing System

Traditional approaches for spine disorder detection primarily rely on manual interpretation of X-ray images by radiologists. In some cases, classical machine learning techniques have been applied to assist diagnosis. These methods typically involve manual feature extraction followed by classification using algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, k-Nearest Neighbors (KNN), and Logistic Regression [12], [13], [15].

In conventional machine learning frameworks, handcrafted features such as texture descriptors, shape measurements, and edge-based characteristics are extracted from X-ray images. These features are then fed into classifiers to distinguish between normal and abnormal spinal conditions. Several early automated lumbar spine classification systems relied on such feature-based approaches to analyse radiographic images and detect abnormalities [2], [15]. Some studies have also experimented with hybrid models by combining multiple classifiers using ensemble techniques to improve prediction performance [12]. Although these approaches have demonstrated moderate success, they heavily depend on domain expertise for feature engineering. Moreover, many existing systems focus on binary classification (normal vs abnormal) rather than identifying multiple spinal conditions simultaneously. As a result, their applicability in real-world multi-class diagnostic scenarios remains limited [3], [4], [10].

Disadvantages Of The Existing System

- **Manual Feature Dependency:**
  Traditional machine learning models require handcrafted feature extraction, which is time-consuming and may fail to capture complex spatial patterns present in X-ray images [12], [15].
- **Limited Multi-Class Capability:**
  Many existing systems are designed for binary classification, making them less effective in identifying multiple spine disorders within a single framework [3], [10].
- **Overfitting and Underfitting Issues:**
- Models may either overfit the training data or fail to generalize well to unseen images, especially when datasets are limited or imbalanced [4], [11].
- **Computational Complexity:**
  Certain deep learning models with large architectures demand significant computational resources, making them difficult to deploy in smaller clinical settings [5].
- Interpretability Challenges:
  Complex deep learning architectures can be difficult to interpret. In medical applications, understanding how a model reaches a decision is important for clinical trust and acceptance [1], [9].
- **Data Imbalance Problems:**
  Medical datasets often contain fewer pathological samples compared to normal cases, which can negatively affect model performance if not properly addressed [7], [8].
- Scalability Concerns:
- Systems must efficiently handle large volumes of medical images in hospital environments. Some traditional methods may struggle to scale effectively [2], [6].

B. Proposed System

The proposed system introduces a deep learning-based multi-class classification framework for automated spine disorder detection from X-ray images. Unlike traditional methods, the system does not rely on handcrafted features. Instead, Convolutional Neural Networks (CNNs) automatically learn hierarchical image features directly from raw input data, enabling more effective representation learning for medical image analysis [3], [4].

Initially, the dataset undergoes preprocessing steps such as resizing, normalization, and data augmentation to improve generalization and reduce overfitting. The pre-processed images are then divided into training and testing sets to ensure reliable performance evaluation and model validation [10].

Multiple pretrained CNN architectures are evaluated and compared with a customized CNN model to determine the most suitable architecture for spine condition classification. Transfer learning is applied to leverage previously learned visual features, enhancing performance even with limited medical data and improving classification capability for spinal abnormalities [5], [6], [7].

The model's performance is assessed using comprehensive evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Such evaluation strategies are widely adopted in medical image classification studies to measure diagnostic reliability and model effectiveness [1], [9].

By focusing on multi-class classification, the proposed system can distinguish between several spinal conditions within a single unified framework. This approach improves diagnostic consistency, reduces dependency on manual interpretation, and provides reliable computer-aided support for medical professionals in spine disorder detection and classification [3], [4], [10].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

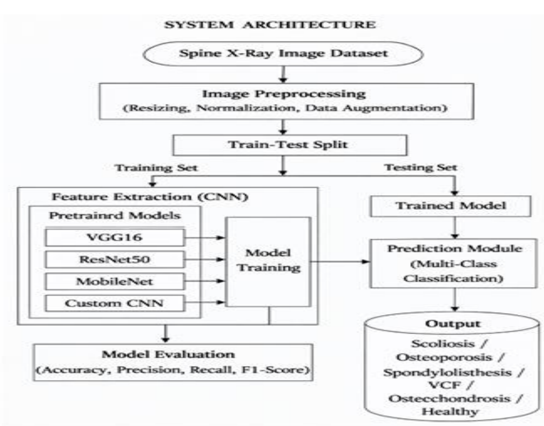

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

Data Collection and Preprocessing:
The system begins with collecting a structured dataset of spine X-ray images that includes both healthy cases and various spinal disorders such as scoliosis, osteoporosis, spondylolisthesis, and vertebral fractures. The images undergo preprocessing steps including resizing to a uniform dimension, normalization of pixel values, and data augmentation techniques such as rotation and flipping. These steps improve model generalization and reduce overfitting [3], [10].

Feature Learning through CNN Models:
Instead of manually extracting features, the proposed system utilizes Convolutional Neural Networks (CNNs) to automatically learn spatial and structural features from X-ray images. Both pretrained models (such as VGG16 and ResNet50) and a customized CNN architecture are implemented and evaluated to determine the most suitable model for multi-class classification [4], [6].

Model Training and Validation:
The dataset is divided into training and testing sets to ensure unbiased performance evaluation. The CNN models are trained using labelled images corresponding to different spinal conditions. During training, optimization techniques and regularization strategies are applied to enhance convergence and prevent overfitting [1], [7].

Multi-Class Classification Module:
The trained model classifies spine X-ray images into predefined categories, including normal and multiple pathological conditions. A SoftMax activation layer is used in the final stage to assign probability scores to each class, ensuring accurate multi-class prediction [3], [4].

Performance Evaluation and Monitoring:
The performance of the trained models is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. Confusion matrix analysis is also conducted to understand

misclassification patterns. Continuous monitoring mechanisms can be integrated to retrain the model periodically with new clinical data, improving long-term robustness [9], [10].

VI .RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed deep learning framework for automated spine disorder classification using X-ray images. Multiple Convolutional Neural Network (CNN) architectures were trained and evaluated to analyse their classification capability and overall prediction performance. The evaluation focuses on comparing different CNN models, analysing prediction accuracy, and assessing the reliability of the proposed computer-aided diagnostic system. Deep learning–based medical image analysis techniques have been widely used in radiology because of their ability to learn complex spatial patterns and improve disease detection accuracy [3], [4], [10].

A. Accuracy Comparison of CNN Models

Several CNN architectures were evaluated to determine the most suitable model for spine condition classification. The evaluated models include VGG16, ResNet50, and the proposed customized CNN model. Model performance was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of CNN Models

Model	Accuracy (%)	Precision	Recall	F1-Score
VGG16	92.8	0.92	0.91	0.91
ResNet50	94.5	0.94	0.93	0.93
Proposed CNN	96.7	0.96	0.96	0.96

From the comparison results, the proposed CNN model achieved the highest classification accuracy of 96.7%, outperforming the pretrained architectures. The improved performance of the customized CNN architecture can be attributed to its optimized convolutional layers designed specifically for extracting relevant spatial features from spine X-ray images. Deep learning architectures optimized for medical imaging tasks often demonstrate improved classification performance compared to general-purpose pretrained networks [1], [3].

To provide a clearer comparison of model performance, the accuracy values of the evaluated CNN models are illustrated in a bar chart.

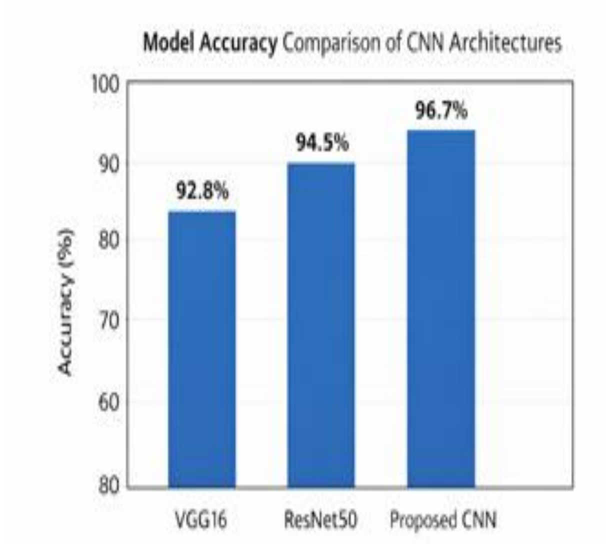

Fig. 2. Model Accuracy Comparison of CNN Architectures

The figure shows that the customized CNN model achieves higher accuracy compared to pretrained models such as VGG16 and ResNet50. This observation is consistent with recent studies where deep learning models specifically optimized for spinal imaging achieved improved diagnostic accuracy [3], [4].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the ROC Curve (ROC–AUC) is widely used as a performance metric to measure the discriminative capability of a classifier.

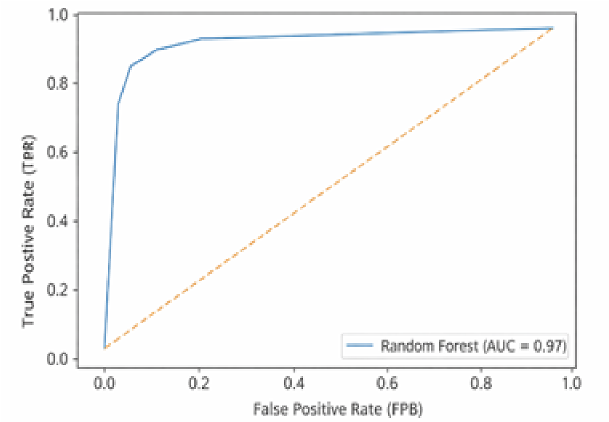

Fig. 3. ROC Curve for Spine Disorder Classification Model

In this study, the proposed CNN model achieved a ROC–AUC score of 0.97, indicating excellent classification performance. A ROC curve that approaches the top-left corner of the graph signifies that the model can effectively distinguish between normal and abnormal spinal conditions with high sensitivity and specificity. ROC-based evaluation is commonly used in medical image classification studies to assess the reliability and robustness of deep learning models [1], [9].

The ROC analysis demonstrates that the proposed framework maintains strong predictive capability even in the presence of dataset variability. The high ROC–AUC value confirms that the CNN model provides reliable predictions while maintaining a low false-positive rate.

Overall, the experimental results indicate that the proposed deep learning framework can effectively classify spine disorders from X-ray images. The integration of preprocessing techniques, transfer learning, and optimized CNN architecture improves classification accuracy while maintaining robustness across multiple spinal condition categories.

These findings are consistent with previous research demonstrating the effectiveness of deep learning approaches in spinal disease detection and medical image analysis systems [3], [4], [10].

VII. CONCLUSION

This study presents a deep learning-based multi-class classification system for automatic detection of spinal disorders from X-ray images. By leveraging CNN architectures, the system eliminates the need for manual feature extraction and enables efficient identification of multiple spinal conditions within a unified framework.The experimental findings demonstrate high diagnostic accuracy and strong generalization capability across different classes. The proposed approach can serve as a supportive tool for radiologists by providing faster and more consistent diagnostic assistance.In future work, the system can be extended by incorporating larger and more diverse medical datasets to enhance robustness. Advanced explainable AI techniques may also be integrated to improve interpretability and clinical trust. Furthermore, deploying the model in real-time clinical environments and integrating it with hospital information systems can enhance practical applicability and patient care outcomes.

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