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Deep Learning-Based Analysis of Vertebrae X-ray Images

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Abstract: *Vertebral disorders such as scoliosis and spondylolisthesis are becoming increasingly common due to sedentary lifestyles, making early diagnosis critical for effective treatment and management. Traditional X-ray techniques are often time-consuming and susceptible to errors. This study introduces a custom Convolutional Neural Network (CNN) designed to classify vertebrae X-ray images into three categories: Normal, Scoliosis, and Spondylolisthesis. Utilizing a dataset of 338 subjects, the model achieved a training accuracy of 91.25% and a validation accuracy of 88%. The precision scores were 85% for Scoliosis, 83% for Normal, and 100% for Spondylolisthesis, accompanied by F1-scores of 88%, 83%, and 93%, respectively. The model demonstrates robust diagnostic performance, particularly for scoliosis and spondylolisthesis, providing a more efficient and accurate tool for early diagnosis that can significantly enhance patient outcomes.*

Keywords: vertebral disorders, scoliosis, spondylolisthesis, Convolutional Neural Network, validation accuracy, precision, F1- score

I. INTRODUCTION

The vertebral column, consisting of 33 vertebrae, plays a vital role in supporting human movement, maintaining stability, and protecting the spinal cord. Degenerative conditions such as scoliosis and spondylolisthesis can significantly reduce quality of life by causing pain and limiting mobility. Scoliosis is characterized by an abnormal curvature of the spine, commonly diagnosed through X-ray imaging using the Cobb angle, with a measurement greater than 10° indicating the condition. Spondylolisthesis occurs when one vertebra slips forward over the one below it, often leading to symptoms like difficulty standing or walking. Traditional diagnostic methods often rely on measuring biomechanical features such as the Cobb angle or pelvic incidence. These processes can be time-consuming, susceptible to human error, and require specialized expertise. Furthermore, depending solely on these biomechanical parameters can introduce cumulative errors, lowering diagnostic accuracy and efficiency. Recent advancements in artificial intelligence (AI) and deep learning (DL) have paved the way for automated diagnostic systems. Unlike conventional methods, our model eliminates the need for manual feature extraction and biomechanical measurements. Instead, it utilizes the powerful feature extraction capabilities of convolutional neural networks (CNNs) to accurately and efficiently classify spinal disorders. This approach streamlines the diagnostic process, reducing reliance on multiple imaging modalities and specialized tools. By automating the classification of spinal disorders, it enhances both the speed and accuracy of diagnoses, ultimately improving patient outcomes. This research develops a custom deep learning model for the classification of X-ray images into three categories: Normal, Scoliosis, and Spondylolisthesis. Our approach achieves an 88% validation accuracy without relying on biomechanical markers like the Cobb angle. The key contributions of this paper include the development of a custom deep learning model for automated spinal disorder detection without manual feature extraction. This innovative method demonstrates significant potential for enhancing diagnostic efficiency, improving patient care, and facilitating early intervention strategies in clinical settings. Future work will focus on expanding the dataset to include more varied cases and exploring transfer learning techniques to further enhance model performance. Ultimately, the goal is to integrate this automated system into clinical practice, aiding healthcare professionals in making more accurate and timely diagnoses, thereby improving overall patient outcomes.

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II. RELATED WORK

Several studies have explored AI and deep learning for spinal disorder detection. Traditional approaches typically rely on measuring biomechanical parameters such as the Cobb angle and vertebral alignment. For instance, the Cobb angle is often used to assess scoliosis severity, while spondylolisthesis is determined through vertebral slippage measurements. However, these methods can be time-consuming, errorprone, and require expert knowledge for accurate interpretation. Recent advancements have increasingly integrated machine learning and deep learning techniques to enhance diagnostic accuracy in the medical field. Pretrained models, such as DenseNet-201 and Res-Net, have become highly popular due to their robust feature extraction capabilities and adaptability across different types of image data. These models have yielded remarkable results in classifying medical images, particularly in diagnosing spinal conditions like scoliosis and spondylolisthesis. However, one limitation of these pretrained models is their reliance on knowledge transfer from non-medical datasets, which may not fully capture the nuances and intricacies of medical imaging, potentially restricting overall performance when applied to specific healthcare problems. Our work offers a distinct approach by developing a custom deep learning model specifically designed for analyzing spinal X-ray images. This model eliminates the need for traditional manual feature extraction or reliance on biomechanical measurements like the Cobb angle, which are often time-consuming and prone to human error. By leveraging convolutional neural networks (CNNs), our model provides an automated, efficient, and highly accurate solution for diagnosing spinal conditions, offering a promising alternative to conventional methods.

III. METHODOLOGY

A. Data Collection and Preprocessing

The initial step involves collecting a diverse dataset of vertebrae X-ray images categorized into three classes: Normal, Scoliosis, and Spondylolisthesis. This dataset is sourced from King Abdullah University Hospital, encompassing images of 338 subjects. Following collection, preprocessing is performed to enhance image quality and uniformity. Each image is resized to a standard dimension of 224x224 pixels and converted to grayscale to reduce computational complexity. An Image Data Generator is employed to augment the dataset, applying techniques such as rescaling, shearing, zooming, and flipping to increase the robustness of the model. This augmentation process generates variations of the training images, thereby improving the model's ability to generalize to unseen data. By introducing these transformations, the model becomes less sensitive to specific orientations and scales of the input images, which mimics real-world variations.

B. Model Development

In this step, a Convolutional Neural Network (CNN) architecture is designed to classify the X-ray images. The model comprises multiple convolutional layers followed by max pooling layers to extract relevant features while reducing spatial dimensions. Each convolutional layer employs a combination of different filter sizes to capture various features such as edges, textures, and shapes, which are critical for effective classification. Dropout layers are included to mitigate overfitting during training, randomly deactivating a fraction of neurons to enhance the model's ability to generalize. The final layers consist of a fully connected layer that synthesizes the extracted features and an output layer with a softmax activation function to produce class probabilities for each of the three categories: Normal, Scoliosis, and Spondylolisthesis. The model is compiled using categorical cross-entropy as the loss function, which is well-suited for multi-class classification problems. The Adam optimizer is chosen for efficient training, as it adapts the learning rate based on the first and second moments of the gradients, leading to faster convergence. Additionally, to further enhance model performance, early stopping is implemented as a callback during training, allowing the process to terminate when validation performance ceases to improve. This approach helps prevent overfitting and ensures that the model is trained optimally.

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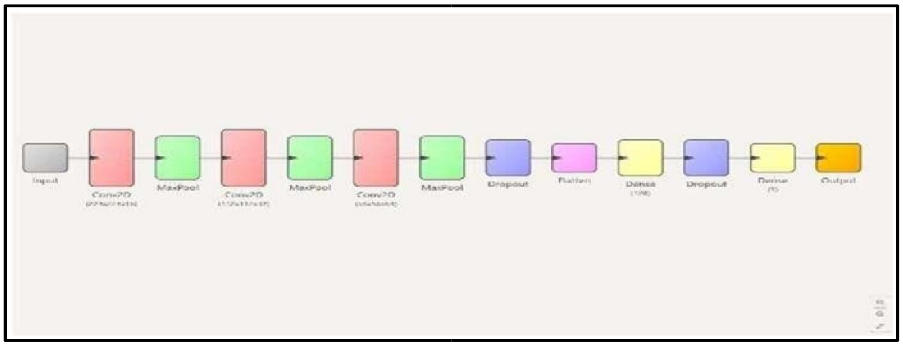

Fig. 1: Architecture for the Custom model used

Additionally, to enhance model performance, batch normalization is applied after each convolutional layer, which helps stabilize the learning process and accelerate convergence by normalizing the outputs. This normalization mitigates internal covariate shift, allowing for higher learning rates and improving overall training efficiency. Furthermore, early stopping is implemented as a callback during training, allowing the process to terminate when validation performance ceases to improve, which helps prevent overfitting and ensures that the model does not train excessively on the training data. Through careful architectural design, including the specified number of layers, configurations, and the strategic incorporation of regularization techniques, the CNN is positioned to deliver high accuracy in classifying vertebrae X-ray images while maintaining robustness against overfitting and generalizing well to unseen data.

C. Model Training and Validation

In this step, a Convolutional Neural Network (CNN) architecture is designed to classify the X-ray images. The model comprises multiple convolutional layers followed by max pooling layers to extract relevant features while reducing spatial dimensions. Each convolutional layer employs a combination of different filter sizes to capture various features such as edges, textures, and shapes, which are critical for effective classification. Dropout layers are included to mitigate overfitting during training, randomly deactivating a fraction of neurons to enhance the model's ability to generalize. The model is compiled using categorical crossentropy as the loss function, which is well-suited for multi-class classification problems. The Adam optimizer is chosen for efficient training, as it adapts the learning rate based on the first and second moments of the gradients, leading to faster convergence. Furthermore, the use of a validation split allows for thorough evaluation at each epoch, ensuring that the model maintains a balance between learning and generalization. The overall training process is documented meticulously to track changes in hyper parameters and their effects on performance. This comprehensive approach to model training and validation ensures a well-rounded evaluation, ultimately leading to a more robust model for classifying vertebrae X-ray images.

D. Evaluation and Visualization

After training, the model is evaluated on a separate test set to measure its performance. Predictions are made, and metrics such as accuracy, precision, recall, and F1-score are computed using the confusion matrix and classification report. Visualization techniques are employed to analyze results, including accuracy and loss plots over epochs and a confusion matrix heat map to illustrate the model's performance across different classes. This comprehensive evaluation provides insights into the model's effectiveness in diagnosing vertebrae conditions.

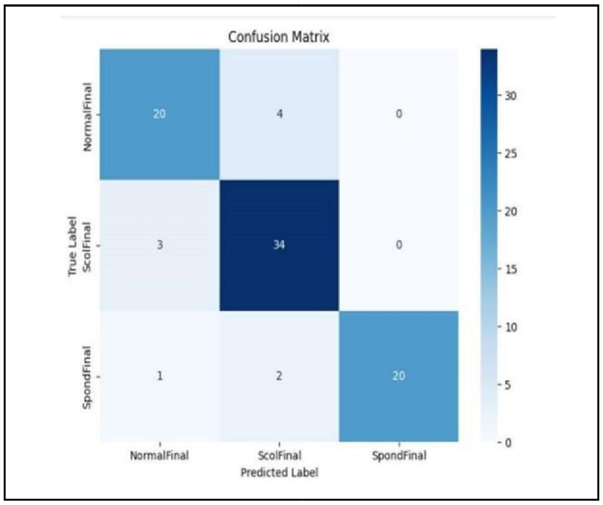

Fig. 2: Confusion Matrix of the model

IV. RESULTS

The proposed deep learning model for classifying vertebrae Xray images demonstrated commendable performance across three categories: Normal, Scoliosis, and Spondylolisthesis. The classification report indicates that the model achieved a precision of 0.83 and recall of 0.83 for the Normal class, reflecting an accurate identification of Normal cases. For Scoliosis, the model exhibited improved metrics with a precision of 0.85 and recall of 0.92, indicating strong performance in identifying Scoliosis cases. The Spondylolisthesis class achieved perfect precision at 1.00, with a recall of 0.87, showcasing effective classification for Spondylolisthesis. Overall, the model's accuracy was 88%, signifying that it correctly classified 88% of the total instances in the test dataset. The macro average metrics were 0.89 for precision, 0.87 for recall, and 0.88 for F1-score, while the weighted averages were similarly high, reinforcing the model's reliability across different classes. The confusion matrix further validated these findings, showing a significant number of true positive predictions for each category. Additionally, the model's performance suggests its robustness in handling class imbalances, particularly for Scoliosis, where it effectively captured a majority of the positive cases.

Classification Report

	precision	recall	f1-score	support
NormalFinal	0.83	0.83	0.83	24
ScolFinal	0.85	0.92	0.88	37
SpondFinal	1.00	0.87	0.93	23
accuracy			0.88	84
macro avg	0.89	0.87	0.88	84
weighted avg	0.89	0.88	0.88	84

Fig. 3: Classification Report of the model

The high F1-scores across classes demonstrate the model's ability to maintain a balance between precision and recall, minimizing false positives and negatives, which is essential for clinical decision-making. Furthermore, the results imply that the model can serve as a reliable tool for radiologists, aiding in the diagnostic process and potentially reducing the time required for analysis. This could lead to improved patient outcomes by facilitating timely and accurate interventions based on the analysis of vertebrae conditions. These findings underscore the necessity for ongoing research to enhance the model's generalizability across diverse patient populations and imaging conditions. By systematically addressing the identified weaknesses, future iterations of the model could incorporate additional training data or advanced techniques, such as transfer learning, to improve accuracy.

V. CONCLUSION

This research presents a deep learning-based approach for the automated classification of vertebrae X-ray images into three critical categories: Normal, Scoliosis, and Spondylolisthesis. The proposed model demonstrated impressive performance metrics, achieving an overall accuracy of 88% and high precision and recall values across all classes. The results highlight the model's effectiveness in accurately distinguishing between different vertebrae conditions, particularly excelling in the identification of Spondylolisthesis. The findings underscore the potential of deep learning technologies in enhancing diagnostic accuracy and efficiency in clinical settings. By leveraging automated analysis, the model can assist radiologists in making timely and informed decisions, ultimately improving patient care. Moreover, the ability to handle class imbalances and maintain a balance between precision and recall further emphasizes the robustness of the model, making it a valuable tool for medical imaging. Future work may involve refining the model architecture, exploring advanced data augmentation techniques, and validating the model on larger, more diverse datasets to enhance its generalizability. Additionally, integrating the model into clinical workflows could facilitate real-time analysis of X-ray images, thereby advancing the field of radiology and contributing to more effective diagnostic practices. Overall, this study paves the way for the integration of artificial intelligence in healthcare, promising improved outcomes in the diagnosis of vertebral conditions.

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