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Research Paper

AUTOMATED DETECTION OF SPINAL LESIONS FROM CT SCANS VIA DEEP TRANSFER LEARNING

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ABSTRACT— Automated detection of spinal lesions from Computed Topographies (CTs) can significantly enhance diagnostic efficiency and accuracy. This project implements a Computer-Aided Detection (CADe) system for spinal lesion analysis using the Xception model. The system is equipped with an intuitive web-based interface developed using the Flask framework, allowing physicians to seamlessly integrate it into their diagnostic workflow. The CADe system processes input CT scans by extracting vertebral regions of interest, converting them into 2D slices, and performing preprocessing to ensure optimal input quality for the Xception model. The model, fine-tuned with Transfer Learning, classifies vertebrae as either healthy conditions such as metastases, primary tumors, or sclerotic lesions. The training and testing datasets were created from CT scans of patients Records. Data augmentation techniques were applied to expand the dataset and improve model generalization. The Xception model achieved a high accuracy of and a recall of 92.99%, demonstrating its effectiveness in spinal lesion detection. This system aims to provide a reliable and efficient tool to assist medical professionals in spinal lesion diagnosis, enhancing clinical decision-making and patient outcomes.

Index Terms – Spinal lesion detection, computed tomography (CT), Xception, transfer learning, deep learning, vertebra classification, Flask web application, diagnostic imaging.

I. INTRODUCTION

Computer-Aided Detection (CADe) techniques for the analysis of medical images have grown significantly in importance and sophistication. These tools are particularly critical for extensive exams, such as Computed Tomographies (CTs), which cover large sections of the patient's body and demand meticulous attention from medical professionals. Recently, there has been an increasing focus on automated diagnostic tools powered by Artificial Intelligence (AI). Among these, advanced deep learning models have proven highly effective for analyzing CT, MRI, ultrasound, and radiographic images, leading to state-of-the-art performance in various medical tasks, including spinal pathology detection and classification. Spinal metastases, a type of tumor that originates in other organs and spreads to the spine, are a significant diagnostic challenge. It is estimated that 50% to 70% of cancer patients develop bone metastases, with the spine being one of the most commonly affected regions. Diagnosing spinal tumors using 3D imaging such as CT or MRI is particularly challenging due to the intricate structure of the vertebrae and the sheer number of slices requiring analysis. This highlights the urgent need for a fully automated detection system that can accurately and efficiently identify pathological features in the vertebral body. In this project, we present an automated CADe system utilizing the Xception model, a state-of-the-art deep learning architecture optimized for image classification tasks. Leveraging Transfer Learning, the Xception model is fine-tuned to detect abnormalities in vertebrae, including metastases, primary tumors, and other lesions. The system preprocesses CT scans, extracts vertebral slices, and analyzes them for potential anomalies. To enhance usability, the CADe system incorporates a web-based graphical interface developed using the Flask framework, allowing seamless integration into clinical workflows. This Xception-based solution demonstrates high diagnostic accuracy and provides a reliable, efficient tool to support medical professionals in spinal lesion detection, ultimately improving patient outcomes. Deep learning methodologies have shown promising results in cancer detection, segmentation, and classification, see, e.g., the recent survey.

Examples of the different cases of study to which deep learning has been applied include the detection, segmentation, and classification of breast cancer, lung cancer [5], brain tumors, skin lesion [8], liver tumor,

and musculoskeletal disesases. Studies about viral and bacterial pneumonia detection from X-rays were made. Latest research focuses on COVID-19 detection from thoracic CT scans [13], [14], [15]. These works consider different imaging problems, in which the inputs come from CT scans, X-Ray, MRI, or RGB images [8]. These methods use open-source networks like, e.g., UNet [16] and SegNet [17] suitably modified. When dealing with small datasets like in medical applications, training can be a difficult task. For this reason, one of the latest approaches is Transfer Learning, i.e. the practice of using state-of-the-art networks that have already been trained from huge datasets and then transferring the achieved knowledge to another domain. Inspired by these approaches, in this paper, we consider the development of a deep-learning based CADe system for spine lesions in CT scans. Focusing on the spine, a considerable number of studies regard the identification of the vertebral body volume, see, e.g., the work in [18]. In these works, the goal is to identify and label vertebrae, rather than classify eventual diseases. Several works focus on scoliosis and spondylolisthesis detection and classification, see the survey [19], and the recent works [20], [21], [22]. Differently from our work, these approaches do not focus on vertebral lesions. Moreover, papers in [21] and [22] consider X-Ray images, and the work [20] considers ultrasound data. On the other hand, we consider CT scans. As for the segmentation of intervertebral disks, authors in [23] propose a harmonization approach based on GANs. Differently from our approach, they do not consider lesion classification. Moreover, their method is tailored for MRI images. Lumbar diseases are instead considered in [24]. Similarly to our method, authors propose a classification scheme based on VGG networks. However, they mainly focus on MRI images and do not consider vertebral lesions. A grading system for intervertebral disk degeneration is proposed in [25]. Similarly to the work in [24], authors do not consider vertebral lesions, and their approach is tailored for MRI images. As regards spine tumors, the attention is entirely on spine metastases. Several works consider deep learning models for the detection of abnormalities in the spinal column. In [26], authors propose a study of the performances of a Faster R-CNN network on MRI images. In [27] authors exploit Siamese networks to detect spine metastases from MRI images Despite the high performance, the slices have to be manually extracted from the MRI sequences. In [28] MRIs are exploited to label vertebrae

and detect the presence of tumors. However, only 2D slices from the sagittal plane are considered, making small or non centered tumors hard to detect. As regards spine metastasis segmentation, [29], [30] use the UNet neural network on MRI images. Differently from these approaches, in this paper, we consider instead an automatic tool to detect spinal lesions from CT scans rather than MRIs. Also, the proposed methodology does not require manual annotations. As for deep learning methodologies for detection in CT scans, authors in [31] propose an unbalanced UNet for labeling and segmentation of vertebrae, without a particular focus on abnormalities. The work in [32] presents a pipeline based on a region of interest detector and a multi-modal classifier for spinal metastases. Unlike our approach, that study focuses on metastatic epidural spinal cord compression. In [33], authors propose a diagnosis method for benign and malignant vertebral fractures using the ResNet50 network. However, their pipeline relies on sagittal scans and requires human intervention to select the initial region of interest, which differs from our fully automated system. In [34], a deep learning-based tool employing a convolutional network is used for hybrid detection-segmentation of spinal metastases from CT scans. Although effective, this system was tested exclusively on patients with high levels of metastases, without considering healthy controls. In contrast, our approach evaluates both healthy and lesioned vertebrae. The method in [35] focuses on segmenting metastases from manually extracted volumes of interest in CT scans. Our methodology, however, automates this process without requiring manual extraction. Authors in [36] propose a detection system specifically for lytic spinal lesions using a convolutional model, but their approach excludes other lesion types and does not incorporate a Computer Aided Detection (CADe) system for automated diagnosis. Similarly, [37] uses an iterative random forest-based method for detecting and classifying metastatic lesions in sagittal scans, which, while achieving good sensitivity, resulted in numerous false positives.For segmentation and detection of sclerotic metastases, the work in [38] utilizes a watershed algorithm on CT scans of the thoracolumbar spine

II. RELATED WORK

A. The use of deep learning in medical imaging to improve spine care: A scoping review of current literature and clinical applications

Medical imaging is critical for clinical decision-making and is integral to determining treatment indications and surgical outcomes. Various imaging modalities can be used for accurate detection and diagnosis of spinal pathologies [91]. However, despite following similar diagnostic standards, experienced radiologists can arrive at different diagnoses and measurements with error rates estimated to be 3% to 5% [7]. Much higher discrepancy rates are reported in neuroradiology, with variable reads in up to 21% of imaging studies [8]. Therefore, a key challenge in the diagnosis of spine pathology is improving the workflow to diagnose diseases quickly, automatically, and accurately.

Further, medical care costs are increasing [3], and radiologists who train for 5 or more years after medical school represent an expensive and valuable resource. AI tools to augment the performance of radiologists and provide a low-cost tool to prevent errors hold significant promises for improved quality and cost savings.

Reliable treatment planning, precise intervention, and accurate therapy are required when treating spine conditions to achieve optimal outcomes. While modern imaging techniques inform perioperative case management [9], poor outcomes are still frequent. Thus, the development of scalable, perioperative automated assistance tools could help address this challenge.

B. Oncologic Applications of Artificial Intelligence and Deep Learning Methods in CT Spine Imaging

In spinal oncology, integrating deep learning with computed tomography (CT) imaging has shown promise in enhancing diagnostic accuracy, treatment planning, and patient outcomes. This systematic review synthesizes evidence on artificial intelligence (AI) applications in CT imaging for spinal tumors. A PRISMA-guided search identified 33 studies: 12 (36.4%) focused on detecting spinal malignancies, 11 (33.3%) on classification, 6 (18.2%) on prognostication, 3 (9.1%) on treatment planning, and 1 (3.0%) on both detection and classification. Of the classification studies, 7 (21.2%) used machine learning to distinguish between benign and malignant lesions, 3 (9.1%) evaluated tumor stage or grade, and 2 (6.1%) employed radiomics for biomarker classification. Prognostic studies included three (9.1%) that predicted complications such as pathological fractures and three (9.1%) that predicted treatment outcomes. AI's potential for improving workflow efficiency, aiding decision making, and reducing complications is discussed, along

with its limitations in generalizability, interpretability, and clinical integration. Future directions for AI in spinal oncology are also explored. In conclusion, while AI technologies in CT imaging are promising, further research is necessary to validate their clinical effectiveness and optimize their integration into routine practice.

C. *Deep learning system for automated detection of posterior ligamentous complex injury in patients with thoracolumbar fracture on MRI*

This study aimed to develop a deep learning (DL) algorithm for automated detection and localization of posterior ligamentous complex (PLC) injury in patients with acute thoracolumbar (TL) fracture on magnetic resonance imaging (MRI) and evaluate its diagnostic performance. In this retrospective multicenter study, using midline sagittal T2-weighted image with fracture (± PLC injury), a training dataset and internal and external validation sets of 300, 100, and 100 patients, were constructed with equal numbers of injured and normal PLCs. The DL algorithm was developed through two steps (Attention U-net and Inception-ResNet-V2). We evaluate the diagnostic performance for PLC injury between the DL algorithm and radiologists with different levels of experience. The area under the curves (AUCs) generated by the DL algorithm were 0.928, 0.916 for internal and external validations, and by two radiologists for observer performance test were 0.930, 0.830, respectively. Although no significant difference was found in diagnosing PLC injury between the DL algorithm and radiologists, the DL algorithm exhibited a trend of higher AUC than the radiology trainee. Notably, the radiology trainee's diagnostic performance significantly improved with DL algorithm assistance. Therefore, the DL algorithm exhibited high diagnostic performance in detecting PLC injuries in acute TL fractures.

D. *Deep learning-based automated spine fracture type identification with Clinically validated GAN generated CT images*

Automatic type identification of sub-axial spine fractures is of prime importance for orthopedic to reduce image interpretation time and increase patient care time. But identifying fracture types is challenging due to imbalanced datasets. In this work, CT scan images of fractured spine has been collected from a Tertiary Care hospital and extended Deep Convolutional Generative Adversarial Network (DCGAN) architecture is developed for generating spine fracture images that overcomes the imbalanced dataset problem.

These enhanced datasets are clinically evaluated with Two Visual Turing Tests (VTTs): the first test to "identify real and generated images" and second test to determine "type of fractures in the generated images." The first VTT demonstrates that generated images of fractures are realistic and that even spine surgeons have difficulty in distinguishing them from real. The second VTT demonstrates that fracture lines are clearly visible in the generated images. The VTT results are analyzed using Fleiss Kappa statistical techniques to determine the inter observer reliability of spine surgeons' clinical evaluation. The results showed high interobserver agreement for "type identification" in the generated images. The clinically evaluated generated images are provided to the proposed ensemble-based type identification model, which outperformed other models in type identification.

III. PROPOSED METHODOLOGY

The proposed system uses the advanced Xception model, which leverages separable convolutions to improve feature extraction and overall performance. It eliminates the need for manual region selection and can automatically detect and classify a wide range of spinal lesions, including metastases, tumors, and fractures. The system also includes a user-friendly interface built with Flask, allowing medical professionals to easily upload CT scans and receive diagnostic results. Furthermore, the proposed system incorporates advanced preprocessing techniques, such as data augmentation, to enhance its accuracy and adaptability to varying medical imaging data. Overall, the proposed system offers a more automated, accurate, and scalable solution for spinal lesion detection compared to existing methods.

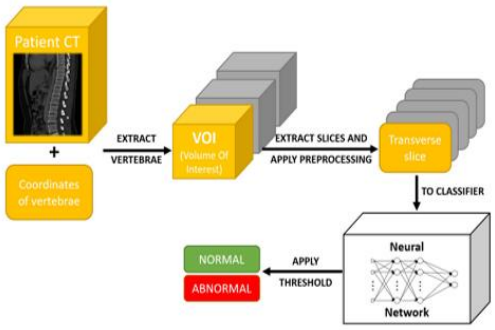


Fig. 1: System Overview

1. Data Collection

This step involves gathering ultrasound image data related to histotripsy ablation. The data could include images of both treated (ablated) and untreated (non-ablated) tissue, usually acquired from patients undergoing the histotripsy procedure or from publicly available datasets.

2. Data Analysis/Load Data

After collecting the dataset, the next step is analyzing and loading the data into the system. This involves checking the quality of the data, ensuring there are no missing or corrupted images, and formatting them correctly for further processing. In this step, the images are typically resized and normalized for consistency.

3. Data Feature Extraction

In this step, the system uses various techniques to extract meaningful features from the ultrasound images. Features such as texture, edges, or regions with high intensity (indicating potential ablation) are identified. This helps the Xception in the next step to learn essential patterns from the images.

4. U-Net Model for Segmentation

The U-Net model is a deep learning architecture specifically designed for image segmentation. It consists of an encoder (which captures feature representations of the image) and a decoder (which reconstructs the segmentation output). The U-Net is used to segment the ultrasound images into regions of ablated and non-ablated tissues, providing a pixel-wise classification.

5. Split Dataset

To train and evaluate the model, the dataset is divided into three parts: training, validation, and testing datasets. Typically, the dataset is split such that 60% is used for training the model, 20% for validating the model during training (to tune hyperparameters), and the remaining 20% for testing the final model's performance.

6. Xception Model for Training

In this step, the Xception model is trained using the segmented images from the U-Net model. The Xception is responsible for learning high-level features from the images and classifying them as ablated or non-ablated tissues. The model uses the images from the training dataset to learn patterns that are then applied to unseen test data.

7. Model Evaluation

After training the Xception, the model is evaluated using the test dataset. Metrics such as accuracy, precision, recall, and the Dice similarity coefficient are used to assess how well the model performs. This step helps in determining whether the model has learned to correctly identify ablation areas and if further tuning or adjustments are needed.

8. Model Save

Once the model achieves satisfactory performance, it is saved for future use. The trained model can be saved as a file (e.g., .h5 or .pkl) and later loaded to make predictions

on new, unseen ultrasound images. Saving the model ensures that it does not have to be retrained every time it needs to be used in a real-time application.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed Xception-based deep transfer learning model accurately detects and classifies spinal lesions from CT scans. The use of transfer learning and data augmentation improves model generalization and diagnostic performance, achieving a recall of 92.99% with high classification accuracy. The integrated Flask-based CADe system enables efficient and user-friendly clinical diagnosis.

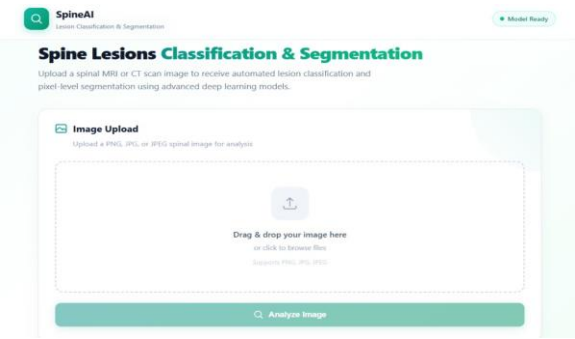


Fig. 2: Upload Image

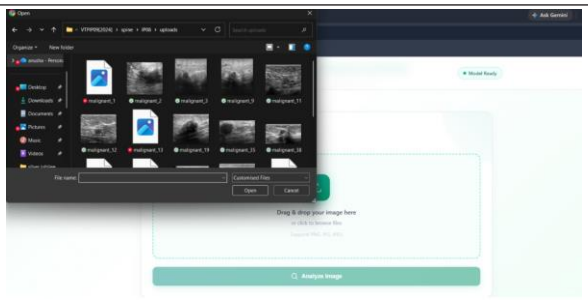


Fig. 3: Choose Image

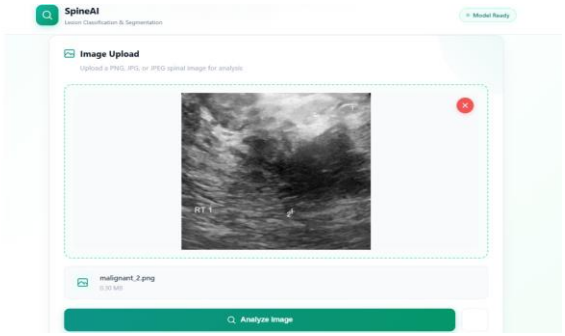


Fig. 4: Analyze Image

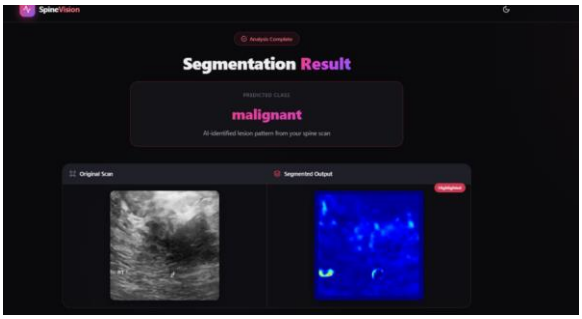


Fig. 5: Results

V. CONCLUSION

In conclusion, the proposed system for the automated detection of spinal lesions from CT scans using the Xception model represents a significant improvement over existing methods. By leveraging deep transfer learning, the system eliminates the need for manual intervention, making the

process faster and more efficient. The use of advanced preprocessing and the Xception model for feature extraction and classification enhances the accuracy and reliability of lesion detection, including a variety of lesion types such as metastases, tumors, and fractures. Additionally, the user-friendly web interface streamlines the diagnostic process, allowing healthcare professionals to review results quickly and make informed decisions. Overall, the proposed system offers a more scalable, accurate, and efficient solution for spinal lesion detection, providing valuable support in clinical decision-making and improving patient outcomes.

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