Advanced AI Framework for Cervical Spine Fracture Detection from CT Scans

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*Abstract*—The rapid and accurate detection of cervical spine fractures from computed tomography (CT) scans is crucial for preventing severe neurological outcomes following spinal injuries. To improve fracture diagnosis by improving image quality through advanced preprocessing techniques and using machine learning algorithms for accurate fracture detection, this paper presents a comprehensive artificial intelligence-based framework. Our methodology begins with preprocessing DICOM images, which includes scaling, CLAHE for contrast enhancement, and unsharp masking to standardize and polish image quality. Subsequent segmentation uses Hounsfield units to concentrate analysis on relevant spinal areas. A Random Forest Classifier predicts fracture locations with great accuracy across cervical vertebrae, demonstrating our system's potential for improving clinical decision-making. This study highlights the importance of precise image processing in enhancing diagnostic performance in medical imaging.

Keywords—Cervical Spine Fractures, Computed Tomography (CT), Image Preprocessing, Segmentation, Medical Imaging, Machine Learning in Healthcare.

# Introduction

The use of computed tomography (CT) has significantly transformed the diagnosis of cervical spine injuries by providing clear imaging crucial for managing spinal fractures. Swift and accurate identification of these fractures is vital for mitigating risks and improving patient outcomes.

In the field of medical diagnostics, the preprocessing of data plays a crucial role in enhancing the quality of information for fracture detection. This project's goal is to create an AI-based system that can predict the presence and location of cervical spine fractures from CT scans, aligning with the RSNA 2022 AI Challenge. The project will delve into the essential preprocessing steps for the CT scans used and the development of convolutional neural networks for fracture prediction, emphasizing the crucial relationship between image preparation and the successful application of AI in medical diagnostics.

# Literature review

## **Cervical Spine Fracture Detection**

Early and accurate detection of cervical spine fractures is crucial to prevent severe neurological outcomes. Cervical spine injuries are commonly assessed using CT imaging due to its ability to provide detailed visualization of bone structures. The rapid and precise identification of fractures can significantly impact clinical decision-making and patient outcomes. High-resolution CT imaging plays a vital role in diagnosing cervical spine fractures, demonstrating superior accuracy compared to single-detector row CT [8].

## **CT Imaging in Spinal Diagnosis**

Computed Tomography (CT) has revolutionized spinal injury diagnosis by providing clear and detailed images of the spine's anatomy. This imaging modality is preferred for its ability to visualize bone structures with high clarity, making it essential for diagnosing fractures. The biomechanical implications of vertebral fractures and the importance of accurate imaging in planning treatment strategies [2]. CT imaging's role in spinal diagnostics has been pivotal in improving patient management and outcomes.

## **Image Preprocessing Techniques**

Preprocessing of CT images is a critical step in enhancing the quality of data for machine learning applications. Techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking are employed to improve image contrast and sharpen edges, respectively. Histogram equalization enhances image contrast while preserving important details [14]. These preprocessing steps are essential for preparing medical images for further analysis and improving the performance of diagnostic models.

## **Machine Learning in Medical Imaging**

The integration of machine learning in medical imaging has shown significant promise in enhancing diagnostic accuracy and efficiency. Machine learning algorithms, particularly deep learning models, have been widely adopted for various medical imaging tasks. Litjens et al. provided a comprehensive survey on the application of deep learning in medical image analysis, highlighting its potential to outperform traditional methods [9]. The future promise of deep learning in medical imaging emphasizing its capability to learn complex patterns from large datasets [5]. Recent research has focused on the application of vision transformers and deep learning models for cervical spine fracture detection, showing significant advancements in accuracy and efficiency [7].

## **Advanced Feature Engineering and Analysis**

Feature engineering is a crucial process in developing effective machine learning models. Selecting relevant features and accurately analyzing them can significantly improve model performance. Guyon and Elisseeff emphasized the importance of feature selection in machine learning, noting that irrelevant or redundant features can degrade model performance [6]. Bolón et al discussed methods for feature selection in high-dimensional data, which is particularly relevant in medical imaging where datasets often contain many features [3].

## **3D Reconstruction and Visualization**

3D reconstruction from CT images provides a volumetric view of anatomical structures, which is essential for comprehensive analysis. Recent advances in 3D reconstruction techniques have improved the accuracy and efficiency of these methods in medical imaging. Virtual reality (VR) and augmented reality (AR) devices are increasingly used for surgical planning and simulation, allowing for precise manipulation of 3D mesh models reconstructed from CT and MRI data. These technologies facilitate detailed preoperative planning and improve surgical outcomes by providing immersive and interactive visualization environments [1]. Additionally, photoacoustic imaging and integration with MRI and CT data enhance the capability for 3D visualization in complex medical cases, improving diagnostic accuracy and treatment planning [11].

## **Model Validation and Real-world Application**

Validating machine learning models in real-world clinical settings is crucial for ensuring their practical applicability. Models need to be tested on diverse datasets and evaluated for their robustness and accuracy in different clinical scenarios. Techniques like cross-validation and hyperparameter optimization are essential for enhancing model performance. Real-world validation through pilot testing and clinical trials is necessary to ascertain the models' efficacy and scalability in clinical practice. Recent studies have highlighted the importance of integrating advanced machine learning models, such as NeckFrac, which uses an ensemble of EffNet and 2.5D UNet + bi-GRU models to achieve high sensitivity and recall in cervical spine fracture detection [13].

# Methodology

## Preprocessing

### Overview

Efficient preprocessing of DICOM images is essential for improving the performance of machine learning models in medical imaging tasks. This study focuses on systematically preparing cervical spine CT scans to enhance the accuracy of fracture detection. The preprocessing process involves resizing, contrast enhancement, and unsharp masking, each customized to address specific challenges presented by the varying quality of medical images.

### Resizing and standardization

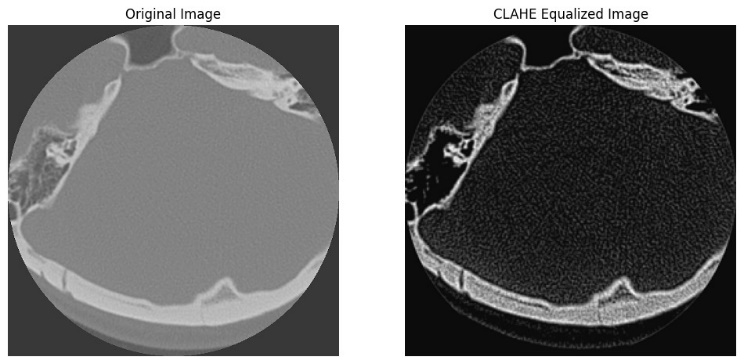
All DICOM images are resized to a uniform resolution of 256x256 pixels. This standardization is critical to ensure consistent input into the convolutional neural networks (CNNs), thereby treating all images equally without biases due to size variations. Bicubic interpolation, known for preserving image quality using higher-order polynomials, is employed for resizing to maintain the clarity of crucial details necessary for accurate fracture detection.

A grey circle with a black background

Description automatically generated

### Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to improve the contrast of the images. CLAHE is preferred over traditional histogram equalization as it prevents overamplification of noise by limiting contrast enhancement in homogeneous areas of the image. This method is particularly advantageous for medical images as it enhances the visibility of fracture lines against the backdrop of varying bone densities and other anatomical structures, which is often challenging in elderly patients due to degenerative changes.



### Unsharp Masking

To further enhance the visual quality of the images, unsharp masking is applied. This technique sharpens the edges by emphasizing contrast at the boundaries between different tissues and bone structures. It operates by subtracting a blurred version of the image from the original image, enhancing the edges and fine details crucial for identifying subtle fractures. The parameters for the unsharp mask—radius and amount—are carefully selected to maximize edge enhancement without introducing artifacts that could mislead the analysis.

A close-up of a scan of a human body

Description automatically generated

### Implementation

The preprocessing pipeline is integrated into a batch processing framework, systematically applying the aforementioned techniques to each image in the dataset. This approach ensures that every image is optimally prepared for the feature extraction and learning phases of model development. The preprocessing steps are integral to our methodology, laying the groundwork for the deployment of advanced machine learning algorithms aimed at matching the diagnostic accuracy of experienced radiologists.

By meticulously preprocessing the images, our aim is to address the inherent challenges posed by the diverse quality of the imaging data collected from multiple international sites. This standardization not only aids in training more robust models but also enhances the generalizability of the system across different clinical settings, ultimately contributing to the goal of improving patient outcomes through faster and more accurate diagnosis of cervical spine fractures.

## Strategic Segmentation of Spinal Images

After meticulously preprocessing DICOM images, our methodology involves a critical segmentation phase. This phase is vital as it isolates the spinal region from other anatomical structures in cervical spine CT scans. This focus improves the accuracy of subsequent fracture detection as it directs analytical efforts to areas of clinical relevance.

#### **Utilization of Hounsfield Units for Precise Segmentation**

We utilize Hounsfield units (HU), a standardized measure of radiodensity, to distinguish between different tissue types during segmentation. The process involves several key steps:

1. Conversion to Hounsfield Units: We convert the pixel values of each DICOM image to Hounsfield units using the image's inherent rescale slope and intercept metadata. This standardization allows for the consistent application of density-based thresholds across varied imaging conditions.

2. Application of Bone Density Thresholds: To specifically target bone structures, we apply a threshold that isolates Hounsfield units indicative of bone density, typically ranging from 300 to 2000 HU. This selective focus ensures that our analysis is confined to the skeletal structure, enhancing the specificity of fracture detection.

3. Refinement through Morphological Operations: We further refine the segmentation by implementing morphological operations, specifically opening, and closing techniques. These operations are executed with a structured kernel, effectively smoothing the segmentation mask, eliminating small artifacts, and improving the continuity of the bone structures. This step is crucial for maintaining the integrity of the spinal anatomy in the segmented images, facilitating more accurate assessments.

Each pixel in the DICOM image is converted to Hounsfield units using the formula:

**HU = pixel value × Rescale Slope + Rescale Intercept**

This conversion standardizes the image data, making it possible to apply universal thresholds for bone density.

A collage of different shapes

Description automatically generated

**Systematic Processing and Archiving**

Our methodology includes a systematic approach to processing and storing segmented images. This ensures consistency and facilitates easy access for future analysis. Each segmented image is methodically saved in designated directories corresponding to their respective categories (e.g., 'train\_segmented' or 'test\_segmented'). This organization supports streamlined retrieval and usage in machine learning model training.

**Visualization for Validation and Quality Assurance**

To validate the quality of our segmentation and ensure its utility for downstream applications, we visually inspect segmented images displayed in a systematic grid format for each case. This step is not merely procedural but serves as a critical quality control measure, allowing for the immediate assessment of segmentation efficacy and the identification of potential anomalies that could impact model training.

## 3D Reconstruction

The segmented spinal images undergo a 3D reconstruction process, providing a volumetric view of the spine which is essential for a comprehensive analysis of its structure and any pathological changes such as fractures.

**3D Mesh Generation:**

1. **Denoising and Image Preparation:**

Before reconstruction, segmented images are denoised using Gaussian blurring to reduce noise and artifacts, ensuring the clarity of the features.

1. **Marching Cubes Algorithm for Mesh Creation:**

We employ the marching cubes algorithm to generate a 3D mesh from volumetric data. This algorithm systematically traverses the voxel grid of the segmented images, creating a polygonal mesh that approximates the surfaces of the spine.

**Dual Visualization Approaches for Enhanced Insight:**

1. **Static Visualization with Matplotlib:**

Using Matplotlib, we render the 3D mesh to provide a static visual representation of the spinal structure. This visualization is crucial for assessing the geometric and spatial relationships within the spine.

1. **Interactive Visualization with Plotly:**

For dynamic exploration, we leverage Plotly to produce interactive 3D visualizations, allowing users to manipulate the visualization by rotating, zooming, and exploring the model in detail, providing an invaluable tool for detailed anatomical studies and educational demonstrations.

The integration of advanced image segmentation and 3D reconstruction into our methodology not only enhances the accuracy of detecting spinal fractures but also significantly enriches the diagnostic process. These techniques offer profound insights into the anatomy and pathologies of the cervical spine, supporting the development of sophisticated diagnostic tools and improving clinical outcomes.

## Machine Learning Model Development in Cervical Spine Fracture Detection

### Model Selection

The use of a Random Forest Classifier is well-suited for this type of classification problem where multiple features influence the outcome. It's robust to overfitting and effective in handling both categorical and numerical data.

### **GroupKFold Approach**

Utilizing GroupKFold is a strategic choice in medical imaging tasks to ensure that the same patient's data does not appear in both training and validation sets, which helps in evaluating the model's performance more realistically.

### **Feature Selection**

The selected features include spatial dimensions (x, y, width, height) and the slice\_number, which are directly relevant to the location and size of the fractures. Including patient\_overall as a feature might help in capturing any overarching patient-specific tendencies or biases in fracture occurrence.

# Results

## Model Performance on Cervical Spine Fracture Detection

The performance of the Random Forest Classifier model was evaluated based on its ability to accurately predict fractures at each of the seven cervical vertebrae (C1 through C7), as well as its overall accuracy in predicting any fracture within the cervical spine region.

### **Accuracy by Vertebra**:

* + **C1**: 90.42%
  + **C2**: 89.49%
  + **C3**: 89.53%
  + **C4**: 89.54%
  + **C5**: 89.90%
  + **C6**: 88.22%
  + **C7**: 86.00%

These accuracies indicate the model's capability to recognize and predict fractures with a high degree of reliability across different segments of the cervical spine, with slightly lower performance observed in the lower vertebrae (C6 and C7).

### **Overall Accuracy:**

The overall accuracy of the model, which represents the average accuracy across all vertebrae, was calculated to be **88.88%**. This metric reflects the model's effectiveness in general fracture detection across the entire cervical region under study.

### **Analysis:**

The results demonstrate that the Random Forest Classifier provides robust performance across most cervical segments. The slightly lower accuracy rates for C6 and C7 may be attributed to the anatomical complexity and variability in fracture presentation at these levels, which could be less distinct than those at higher segments. This suggests potential areas for model refinement, such as incorporating additional imaging features or exploring more sophisticated machine learning algorithms to improve detection sensitivity, particularly for the lower cervical vertebrae.

Furthermore, the high overall accuracy confirms the efficacy of the preprocessing methods and feature selection strategies employed, indicating that the model can effectively leverage the clinical features extracted from CT images to predict fractures. These findings underscore the potential of machine learning models to assist radiologists in the timely and accurate diagnosis of cervical spine injuries, which is crucial for preventing serious neurological consequences.

# Conclusion

In this study, we have developed a detailed framework that combines advanced image preprocessing, segmentation, and machine learning techniques to diagnose cervical spine fractures from CT scans. Our approach enhances fracture detection accuracy by refining image processing techniques and using sophisticated analytical models. We meticulously preprocess DICOM images and apply segmentation using Hounsfield units to focus on clinically relevant areas. The subsequent use of a Random Forest Classifier demonstrates high accuracy in identifying fracture locations across different cervical vertebrae. Integration of 3D reconstruction techniques enhances visual assessment of spinal injuries and supports the clinical decision-making process. The results confirm the effectiveness of our methodology, showcasing significant accuracies in fracture detection across all cervical regions. We aim to continue developing and optimizing our methods to expand the dataset, refine our models, and move towards real-world application through clinical trials and validations. This research not only contributes to the field of medical imaging and artificial intelligence but also sets a benchmark for future studies aiming to integrate these technologies into clinical practice.

# Future Considerations

## **Expanding Collaborative Data Sources**

Enhancing the diagnostic capabilities of our model will involve expanding our dataset through partnerships with global health institutions. By incorporating a broader and more varied dataset that includes data from underrepresented groups and uncommon fracture types, our model will learn to address a more extensive array of clinical scenarios, thereby increasing its robustness and accuracy.

## **Enhancing Model Sophistication**

Although our model currently performs well, there is potential for further enhancement. We intend to investigate more advanced machine learning algorithms, including deep convolutional neural networks and ensemble methods, which may detect more intricate patterns within the imaging data. Optimizing the hyperparameters of our existing Random Forest Classifier and applying techniques like cross-validation are also planned to boost performance.

## **Advanced Feature Engineering and Analysis**

We plan to delve into more sophisticated image processing techniques such as texture analysis and edge detection to identify subtle fractures more effectively. Introducing advanced feature engineering to extract new imaging biomarkers could lead to more profound insights into the specifics of fractures, thereby enhancing the model's sensitivity.

## **Comprehensive Error Analysis**

A detailed analysis of instances where the model fails to perform optimally is essential for ongoing enhancement. Investigating misclassifications and incomplete detections will help pinpoint specific areas of challenge and anomalies that impact the model's effectiveness. These findings will inform further refinements to both data preprocessing and modeling techniques, aiming to elevate the predictive precision and reliability of our framework.

## **Validation and Scalability in Real-world Settings**

Validating the model's efficacy in real-world environments through pilot testing and clinical trials is crucial before its full implementation in clinical settings. This validation will ascertain the model's practical applicability and reveal any potential issues across diverse clinical contexts. Moreover, evaluating the model's ability to scale up to manage vast amounts of data and incorporating feedback from clinical end-users will be crucial for its successful deployment.

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