Bone Segmentation and Tibial Landmark Detection from Knee CT Scans

Introduction

This assignment focuses on the segmentation and landmark detection of the tibial bone from 3D Computed Tomography (CT) image volumes of the knee. The primary goal was to extract accurate segmentation masks of the tibia and identify the lowest medial and lateral anatomical landmarks from the segmented bone.

Problem Statement

Precise identification of anatomical landmarks on bones in medical imaging is important for diagnosis and surgical planning. The tibia, being a load-bearing bone in the lower limb, plays a significant role in orthopedic assessments. Automated analysis using 3D CT data poses challenges due to the complexity of bone structures, variations across individuals, and the need for accuracy. This assignment seeks to simulate such scenarios by requiring accurate detection of key landmarks on the tibial surface, under different segmentation mask conditions.

Objective

The objective of this task is to segment the tibial bone from a 3D CT image of the knee and identify two critical anatomical points:

- The **lowest medial point**, and
- The **lowest lateral point** on the tibial surface.

The assignment requires the detection of these landmarks not only on the original mask but also on modified versions — including expanded and randomized masks. Specifically, the task is to:

- Generate five versions of the tibial mask: Original, 2mm Expanded, 4mm Expanded, Randomized 1, and Randomized 2.

- Detect the medial and lateral lowest points on the tibial surface for each mask.

- Submit the coordinates of the identified points and the corresponding mask files for evaluation.

Data Overview

The input dataset consisted of a single 3D CT image volume of a left knee joint, provided in NIfTI format (left_knee.nii). The image had dimensions of 512 × 512 × 216, where each slice along the z-axis represented an axial CT slice of the knee.

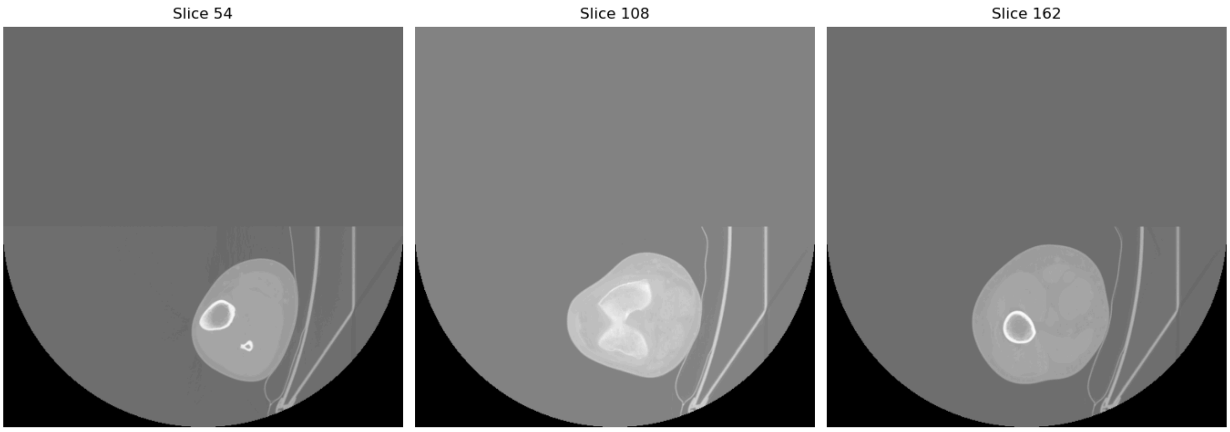

Fig 1: Original masks across three slices

Methodology

Segmentation Mask Handling

We began with the original binary mask of the tibia. To simulate variation and prepare for landmark detection under slightly altered segmentation conditions, the following additional masks were generated:

1. **Original Mask** – the provided tibia mask without any modification.

2. **2mm Expanded Mask** – generated by applying a 2mm morphological dilation, accounting for voxel spacing in all three dimensions.

3. **4mm Expanded Mask** – a more aggressive dilation with a 4mm radius, again respecting voxel spacing.

4. **Randomized Mask 1** – a randomized version created by perturbing the original mask boundary within a 2mm radius, using a fixed random seed.

5. **Randomized Mask 2** – generated similarly but with a different seed to introduce diversity.

All masks were **saved** as .nii.gz files in a dedicated **results/ folder.**

Landmark Detection

The medial and lateral lowest anatomical points on the tibial surface were identified using the following procedure:

- The script iterated through the axial slices from the bottom (highest z-index) upward to find the lowest slice containing tibia pixels.
- The mask on this slice was divided into medial and lateral halves using the centerline of the x-axis.
- For each half, the pixel with the maximum y-coordinate (lowest point in image space) was selected.
- The final coordinates were returned in (x, y, z) format for each of the five masks.

Implementation Details

The implementation was developed using Python, leveraging libraries such as nibabel, numpy, scipy, and matplotlib for medical image processing and visualization. The following steps outline key implementation components:

- Mask Expansion

  To simulate increased segmentation boundaries, the original tibia mask was expanded using morphological dilation. Structuring elements with spherical connectivity were defined based on voxel spacing to achieve 2 mm and 4 mm expansion distances. The function expand_mask_by_distance in src/expansion.py performed this operation.

- Randomized Mask Generation
  Two randomized masks were generated to simulate variability and evaluate robustness of landmark detection. The method applied random deformations via Gaussian noise and morphological operations. The main function for this step was generate_randomized_mask in src/randomize_mask.py.

- Landmark Detection
  For each mask variant, the lowest points on the tibia surface were identified and categorized into medial and lateral sides. The algorithm scanned the inferior-most slice with tibial pixels and divided the mask along the medio-lateral axis. The function detect_lowest_medial_lateral_points in src/landmark_detection.py was responsible for this computation.

Output Submission

The final output included:

- All five tibia segmentation masks saved in compressed NIfTI format

- A CSV file listing the coordinates of the medial and lateral landmarks for each mask

The output filenames and structure were managed to maintain clarity and reproducibility.

Challenges and Observations

While processing, one notable observation was that the detected landmark positions did not vary drastically across the five masks. This is likely because the randomization and expansion operations were mild and largely preserved the lower geometry of the tibial mask, especially around the key anatomical areas where landmarks are expected.

Conclusion

The project achieved its objective of segmenting the tibia and detecting reliable medial and lateral landmarks across multiple mask variations. The approach was systematic and reproducible, following best practices in image processing and 3D medical image analysis.

This work provides a foundational pipeline for tibial landmark detection that can be extended to larger datasets or used as a preprocessing step in orthopedic or surgical planning systems.