Enforcing Explainable Deep Few-Shot Learning to Analyze Plain Knee Radiographs: Data from the Osteoarthritis Initiative

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Objective

The use of fast, accurate, and automatic knee radiography analysis is becoming increasingly important in orthopedics, and it is becoming more important in improving patient-specific diagnosis, prognosis, and treatment. Deep learning medical image analysis has already shown success in a variety of knee image analysis tasks, ranging from knee joint area localization to joint space segmentation and measurement, with almost a human-like performance. However, there are fundamental challenges that stop deep learning methods to obtain their full potential in a clinical setting such as orthopedics. These include the need for a large number of gold-standard, manually annotated training images and a lack of explainability and interpretability. To address these challenges, this study is the first to present an explainable deep few-shot learning model that can localize the knee joint area and segment the joint space in plain knee radiographs, using only a small number of manually annotated radiographs.

Methods

We implemented a deep few-shot pipeline using YOLOv7 and U-Net for 5-shot, 7-shot, and 10-shot knee joint localization and segmentation.

Application: The pipeline aims to enable an explainable deep few-shot learning model that can localize the knee joint area and segment the joint space in plain knee radiographs, using only a small number of manually annotated radiographs

Data Split:

- Multiple few-shot learning datasets were created, each with distinct training, validation, and testing sets.
- There is no overlap in patients between the splits.
- Various augmentations are applied to help with overall generalization

Data Source: All images were collected from the open-access Osteoarthritis Initiative (OAI) dataset (https://nda.nih.gov/oai). These images were then annotated to produce gold-standard annotations for both knee joint space localization and knee joint space segmentation.

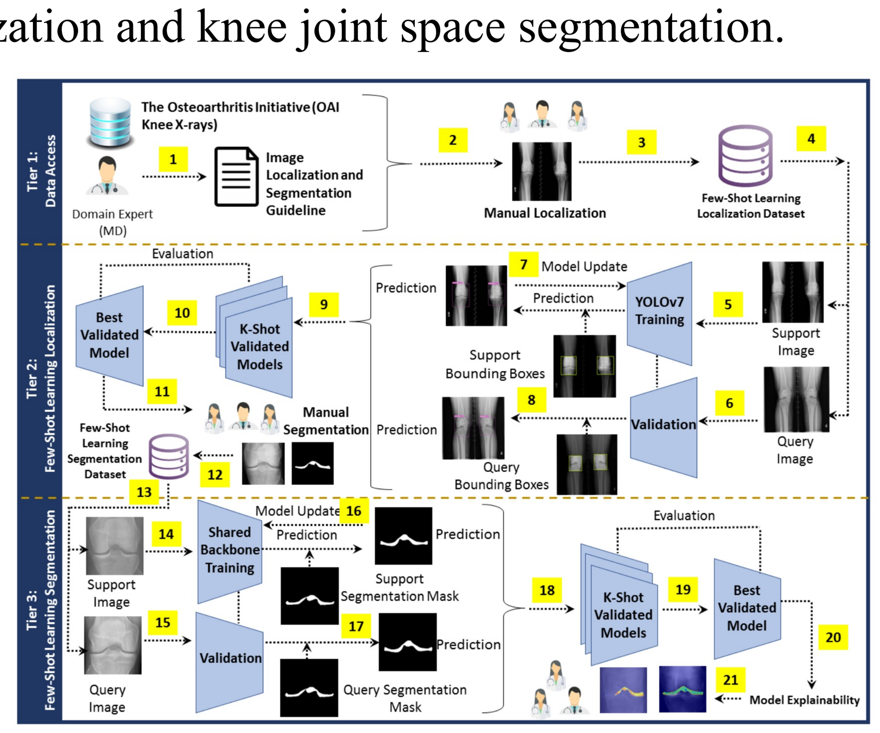

Figure 1. The proposed pipeline for few-shot learning for automatic knee joint area localization and segmentation.

Results

5-shot, 7-shot, and 10-shot knee joint localization and segmentation models were evaluated using intersection over union (IoU) on 50 images for localization and 23 images for segmentation. We found that 10-shot localization and segmentation perform the best with an IoU of 0.94 for localization and an IoU of 0.91 for segmentation.

TABLE I
FEW-SHOT LEARNING LOCALIZATION PERFORMANCE ON THE TEST DATASET, INCLUDING 50 KNEE RADIOGRAPHS.

K-Shot	Average of IoU	mAP@0.5
K = 5	0.57	0.89
K = 7	0.86	0.95
K = 10	0.94	0.98

TABLE II
FEW-SHOT LEARNING SEGMENTATION PERFORMANCE ON THE TEST DATASET, INCLUDING 23 LOCALIZED KNEE RADIOGRAPHS.

K-Shot	Average of IoU
K = 5	0.76
K = 7	0.89
K = 10	0.91

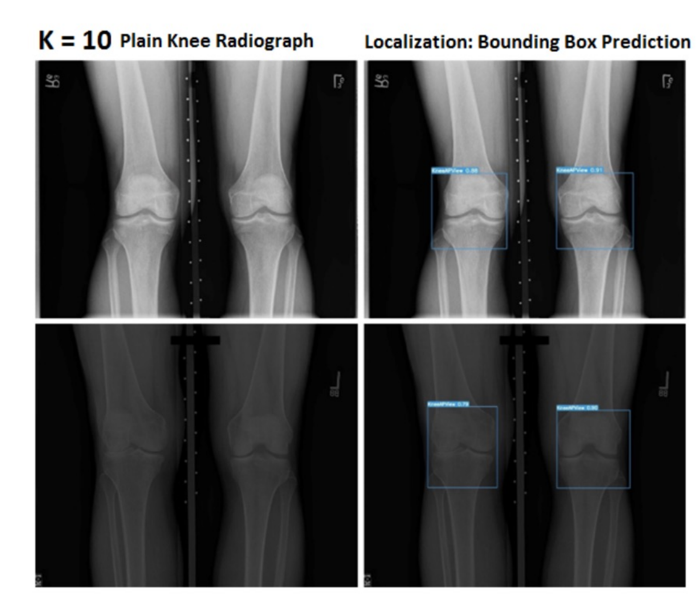

Figure 2. Qualitative and quantitative visualization for knee joint area localization

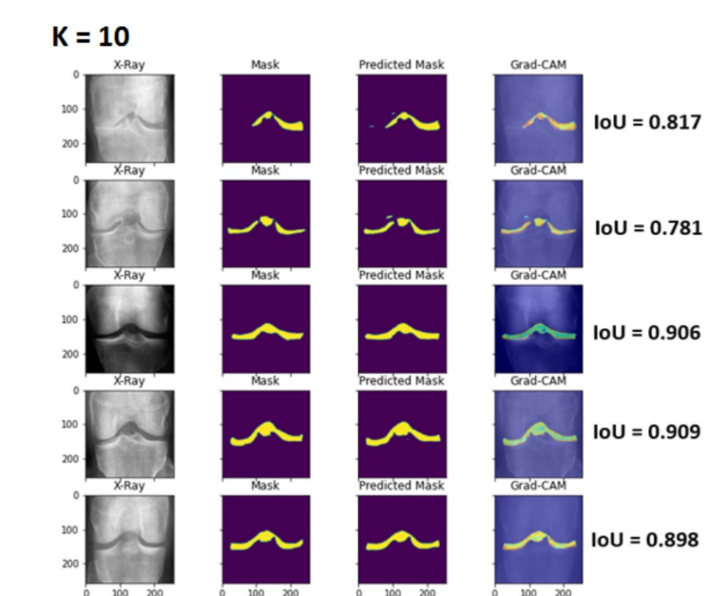

Figure 3. Qualitative and quantitative visualization for knee joint area segmentation.

Conclusion and Outlook

Based on the experimental results, our findings indicate that deep few-shot learning has significant potential for localization and segmentation using only a few manually annotated radiographs. This approach is viable in settings where gold standard annotated is lacking. Despite the methodological strengths of out study, we acknowledge that these methods need to be externally validated before future research or clinical applications. The next step in our pipeline is to automatically measure the joint space width at the medial and lateral parts of the knee joint. Furthermore, we also focus on implementing this pipeline for other anatomical structures (e.g., hip).