Poster ID: 05

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Classification of Femurs in MRI Images from malignant lymphoma patients using deep learning

General Background

Background

Non-Hodgkin's lymphoma (NHL) is a malignant tumor with high morbidity and mortality. MRI images may provide significant information for the diagnosis decision and prognostics prediction of lymphoma.

Motivation

Visual classification of MRI patterns by physicians can be subjective and time-consuming, leading to potential variations in diagnosis and treatment planning. This limitation may result in delays of appropriate therapies, thereby affecting patient outcomes. Moreover, the growing number of NHL cases demands more efficient and precise diagnostic tools to support clinicians in managing their patients effectively.

Target

Classification of three infiltration types in femoral MRI images

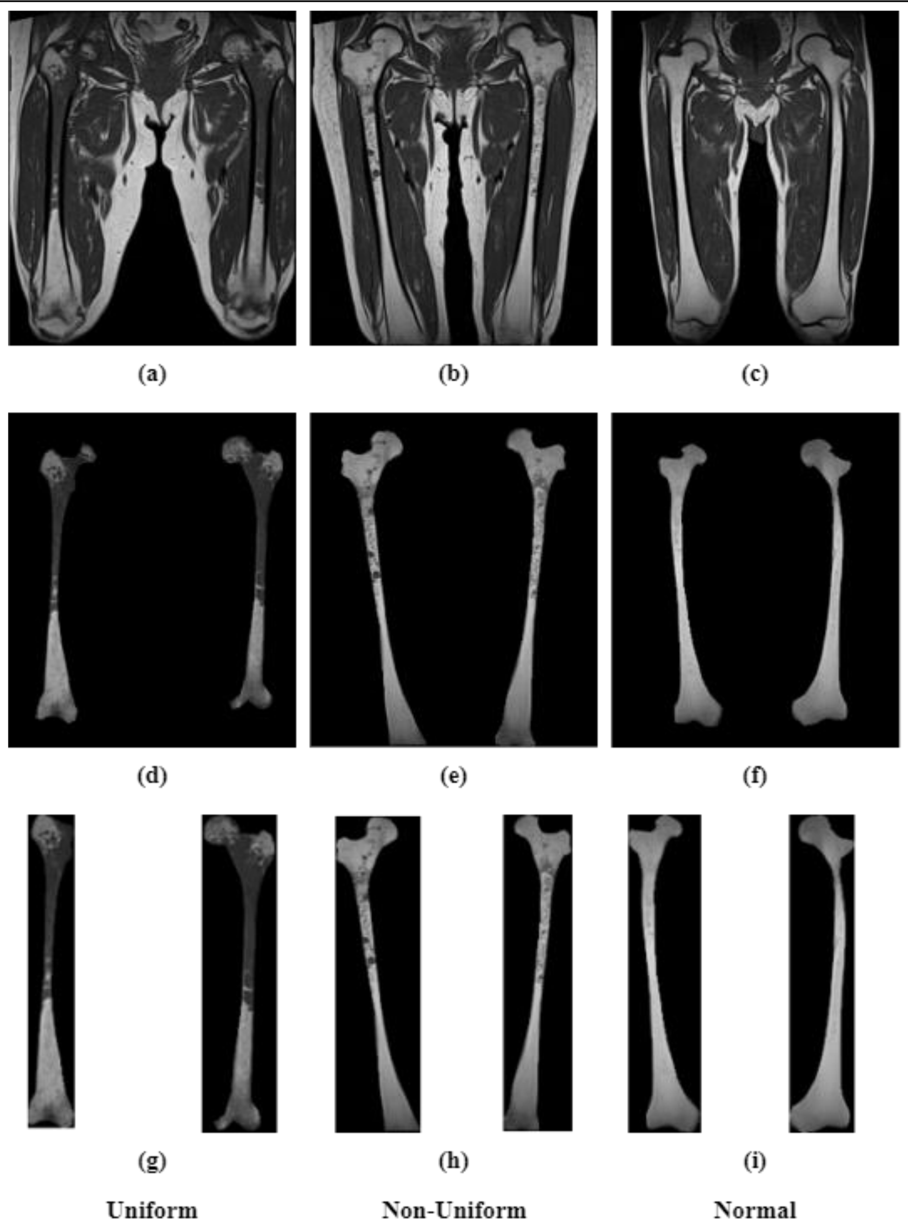

Fig 1. Three Different Types of Femur

Three Different Types of Femur

Fig 1 (a)-(c) illustrate samples of the Uniform femur (Uniform), Non-Uniform femur (Non-Uniform), and Normal femur (Normal), respectively. Fig 1 (d)-(f) are the corresponding segmentation results of Fig 1 (a)-(c), respectively. Fig 1 (g)-(i) are the samples of the unilateral femur patches.

The femur classification is based on the categorization from a previous clinical study[1] and includes three types. The first type is a Uniform femur with a homogeneous low signal region in the bone marrow extending from the proximal to the distal femur; the second is a Non-Uniform femur with a heterogeneous, nodular, and scattered low signal region in the bone marrow; the third is a Normal femur with an absence of a distinct low signal region in the bone marrow.

Materials and Methods

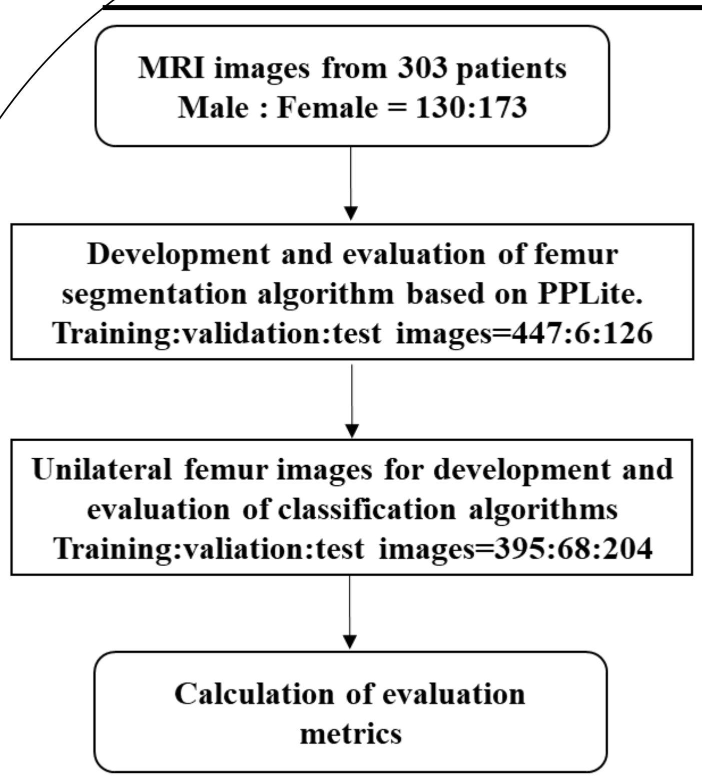

Fig 2. Dataset

As shown in Fig 2, this retrospective cohort study recruited 303 consecutive patients including 130 males and 173 females, aged between 55 and 85 years, diagnosed with lymphoma in 2012-2020 at Aizu Medical Center, Fukushima Medical University.

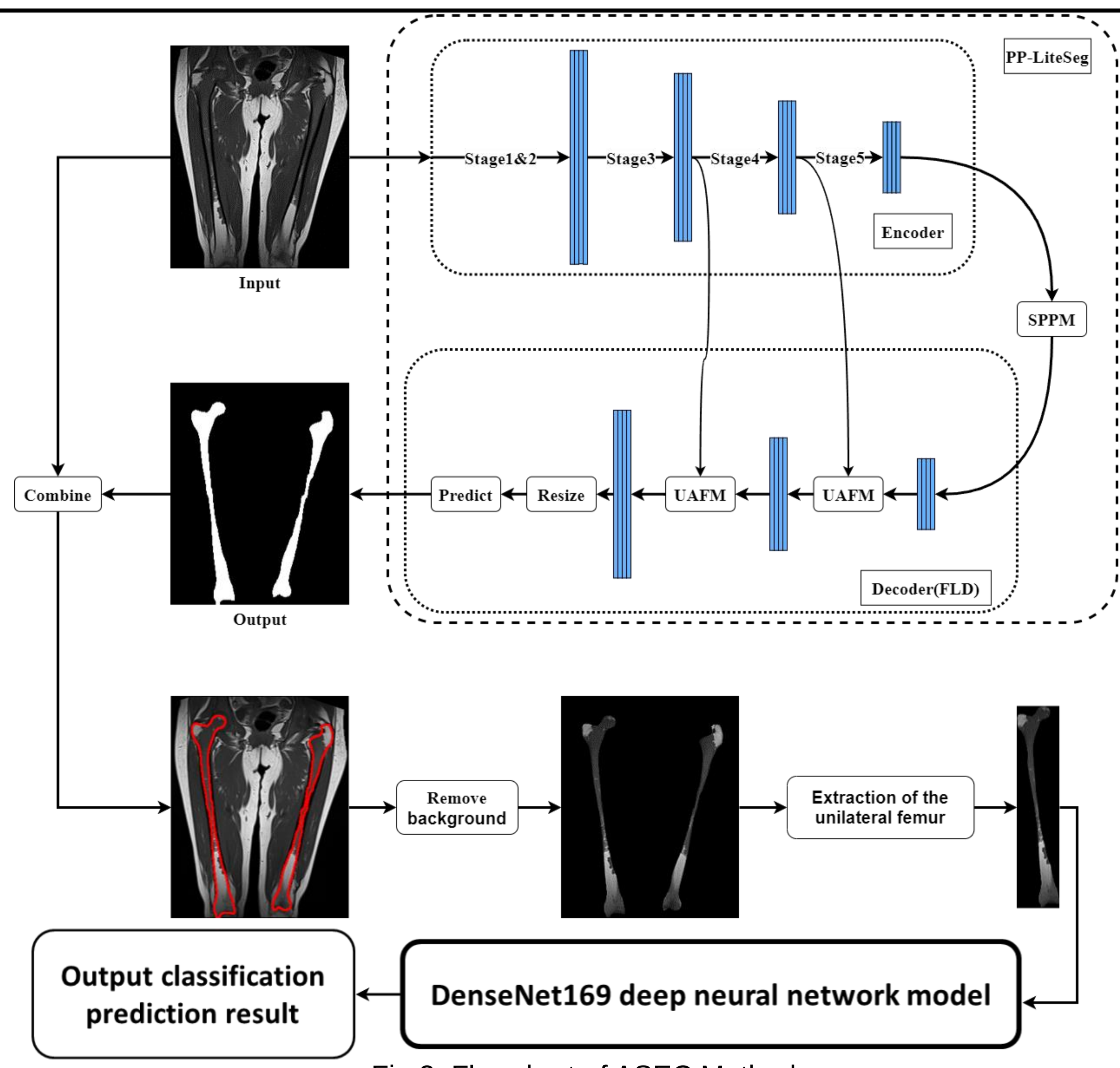

Fig 3. Flowchart of ASEC Method

The first stage involves femoral segmentation from MRI images using PP-LiteSeg. PP-LiteSeg was selected based on our previous research, wherein it demonstrated superior performance compared to other methods such as U-Net, SegNet, and PspNet, achieving an average Dice coefficient of 0.92. PP-LiteSeg utilizes an encoder architecture comprising three novel modules, a Flexible and Lightweight Decoder (FLD), a Unified Attention Fusion Module (UAFM), and a Simple Pyramid Pooling Module (SPPM). The FLD module progressively reduces channel numbers while increasing feature space sizes, balancing computational complexities, and improving model efficiencies. The UAFM module employs both channel and spatial attention mechanisms to enhance feature representation, and accurate segmentation is achieved through multi-level feature fusion. SPPM, as compared to the traditional PPM model, reduces intermediate and output channels, replaces the cat operation with the add operation, and eliminates the shortcut operation, thus increasing its effectiveness[2].

DenseNet169[3] was modified to perform a 3-category classification. The batch size, input size, epoch number, initial warm-up epoch number, and initial learning rate were set to 16, 320, 100, 5, and 0.001, respectively. A stochastic gradient descent method was used to update the models with a cross-entropy loss function. The detailed process flow is shown in Fig 3.

Results

	Segmentation	Unilateral extraction	Accuracy	Macro-Precision	Macro-Sensitivity	Macro-Specificity	Macro-F_1
Original image	—	—	77.8%	75.6%	80.9%	89.3%	78.2%
Segmentation image	✓	—	77.8%	82.4%	76.5%	88.1%	79.4%
Unilateral image	✓	✓	**81.0%**	**84.7%**	**82.7%**	**90.2%**	**83.7%**

Table 1. Classification Results for Each of the Evaluation Parameters by DenseNet169

Table 1 lists the classification indexes of DenseNet169. The highest accuracy of 81.0% was achieved using the unilateral femur dataset and DenseNet169. This combination also achieved the best Macro-Precision, Macro-Sensitivity, Macro-Specificity, and Macro-F1

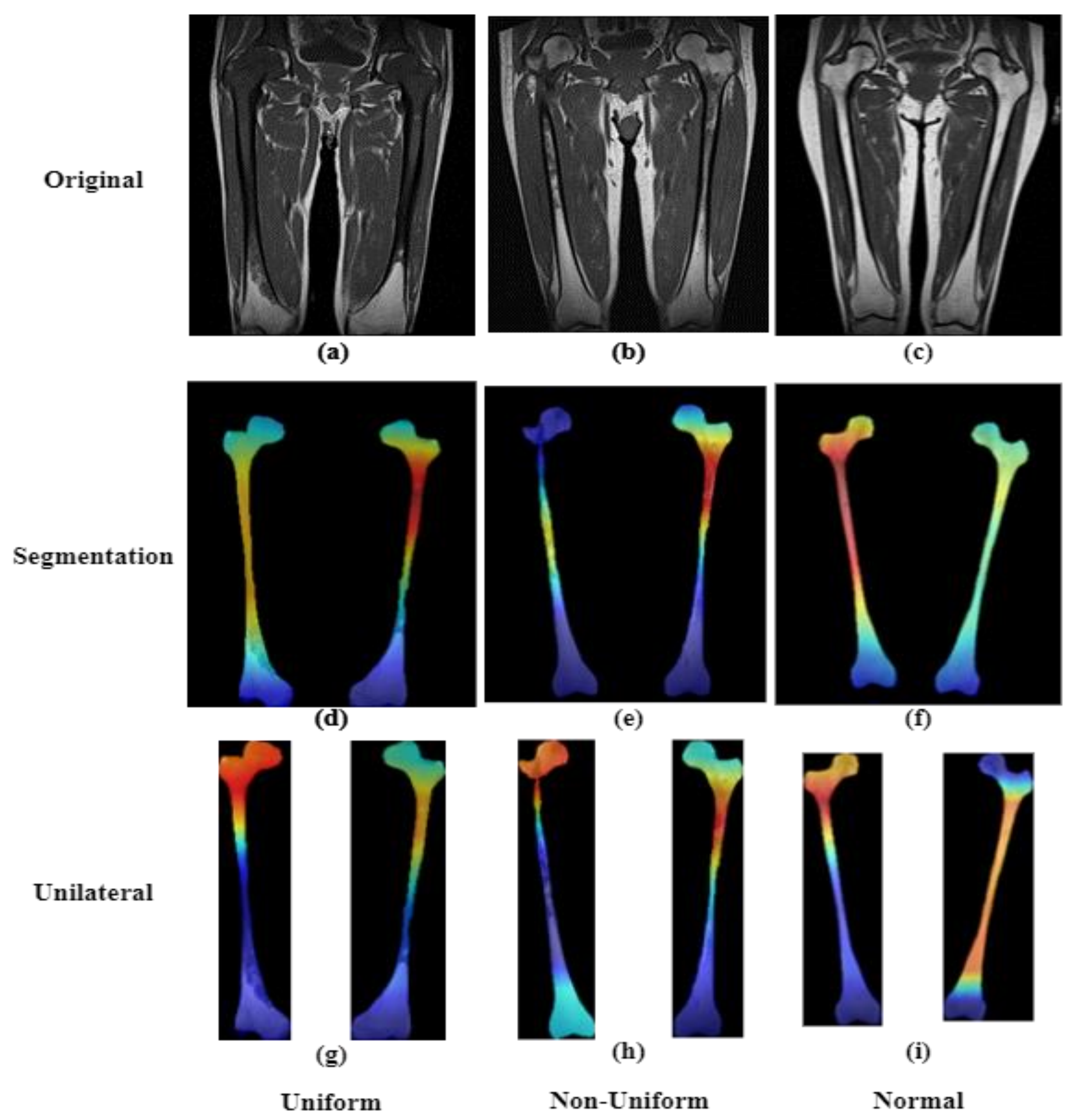

Fig 4. Results with Grad-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM)can achieve to make the neural network-based model more flexible by observing the regions that are more important for estimation. We apply Grad-CAM to the network output layer to determine the location of the network's focus of attention, as shown in Fig 4.

Reference

[1] Ikeda S, Tsunoda S, Koyama D, et al. Femoral marrow MRI is a non-invasive, non-irradiated and useful tool for detecting bone marrow involvement in non-Hodgkin lymphoma[J]. Journal of clinical and experimental hematopathology, 2021, 61(2): 78-84.
[2] Peng J, Liu Y, Tang S, et al. PP-liteseg: A superior real-time semantic segmentation model[J]. arXiv preprint arXiv:2204.02681, 2022.
[3] Iandola F, Moskewicz M, Karayev S, et al. Densenet: Implementing efficient convnet descriptor pyramids[J]. arXiv preprint arXiv:1404.1869, 2014.