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Segmentation of Knee Cartilages in Osteoarthritis using U-Net: Convolutional Neural Network and Age assessment of Patients

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Abstract:Osteoarthritis(OA) is common chronic diseases over the world with knee being the most affected joint. This paper focuses on cartilages of Knee OA. Magnetic Resonance Imaging(MRI) is used for studies, as they provide information related to joint ache and the occurrence and development of OA. The most crucial step in the processing pipeline of musculoskeletal tissues is to obtain quantifiable methods of Knee joint deterioration from MR Images. Here we use CNN based approach, U-Net which has revealed favorable results for segmenting the cartilages. The aim of this study is to illustrate and authenticate the technique for segmenting cartilages of Knee MRI and also assessment of patient's age.

Keywords— Knee OA, Segmentation, U-Net.

I. INTRODUCTION

Osteoarthritis can be defined as degenerative joint disease and osteoarthritis (inflammation inconsistency). It is a disease of the whole joint; articular structures are affected[1]. Based on the population samples the knee pain symptoms are more related to patella volume than other cartilage volumes[2]. Association between femoral cartilage volume changes and tibial cartilage volume changes, in the medial and lateral tibiofemoral joints of patients with radiographically[3]. Using Multivariate Analysis Approach, the amount of cartilage volume damage and fluctuations in pain are associated[4]. Hence, OA is considered to be a disease associated with cartilage structure of Knee.

Magnetic Resonance Imaging (MRI) allow accurate idea of joint structure such as cartilage, bone, ligaments as well as their pathological variations. Latest technology has led to major development in spatial resolution and contrast, allowing researchers to estimate anatomical damage of all the joint structures over sagittal, coronal and axial planes[5]. The cartilage volume and thickness dimensions from MRI interpretation allow us to study the anatomy and biomechanics of arthrodial joints. With the help of radiographic method which allows to rate the changing cartilage loss and also narrowest joint-space width (JSW)[6]capacity.

Joint degeneration are quantitative measures used in the research of OA. Compared to semi quantitative grading scales quantitative measures are advantageous of being purpose and extremely reproducible with a better variety for assessment of tissue deterioration dynamically.

Musculoskeletal Tissue segmentation is key step to gain measures of joint degeneration from MR Images quantitatively. Manual segmentation of tissue is extremely time consuming as the user has to delineate the borders of each joint structure on each MR Image slice, which is repeatedly inclined by the user level expertise[7]. Active shape modelling[8] extracts the Bone Cartilage Interface(BCIs), from which local appearance and edge information is used for segmentation, hence resulting in less average error. Usage of Laplacian thickness measurement was found to be precise.

Multi Atlas segmentation process[9] is a promising tool for segmenting bone and articular cartilage from knee MR image, combined into one segmentation via fuzzy membership and voxel class relaxation. Limitation is introduction of potential measurement bias for creation of knee MRI atlases.

Convolutional Neural Networks are applied for image classification, scene understanding, object tracking and other fields for better results. They surpass human experts in most of the cases related to computer vision problems. The main idea of U-Net neural network is to merge the high-level layers and low-level layers via skip networks, for exact pixel level localization. It comprises of up-sampling and down-sampling; up-sampling propagates great quantity of content information to the higher resolution layer[10].

II. DATASET

The data set used is a collection of 3D images, T1 weighted and nonfat-saturated MR images. Total 150 images are used. All images were provided in the MHD file format, which is very common in the medical field. MHD file will contain raw images and technical Meta information about each image. Among 150 images 74% of the images are training, 13% are testing and 13% are validation set.

III. METHODOLOGY

Ronneberger first introduced U-Net architecture as a method to segment medical images[11]. Strength of this architecture is to capture context by contracting path and accurate localization and spontaneous finding of contour with few parameters than a feed-forward network can be done by enabling symmetric expanding path.

In basic U-Net architecture model, the encoder portion increased the amount of feature maps from 64 to 1024 filters by powers of two at the bottom of "U", the lowest resolution captures the lesion shapes details. The decoder portion, decreases proportionally the amount of feature maps from 1024 to 64, by powers of 2.

Convolution: Each convolutional layer consists of a kernel W which is learned, ReLU unit and a normalization of batch

$r(X) = \max(0, X)$; that is:

$$c(X, W, \gamma) = r(b((X * W)), \gamma) \qquad (1)$$

$b(X, \gamma)$ batch normalization which alter the mean of every channel to 0 and γ the variance to a learn per-channel scale parameter. ReLU component assists gradient propagation and non-linearity. Each convolutional block has a chain of layers $c(X, W, \gamma)$.

A. Augmentation

Image augmentation is a general method to virtually increase the dataset size. In medical imaging, augmentation is performed with transformations that are applied to the images and labels equally. ImgeDataGenerator class of Keras library is used for data augmentation. Augmentation techniques implemented are:

1. Horizontal axis flip is common than vertical axis flip. This augmentation is one of the convenient to implement and has demonstrated usefulness on datasets. Flipping images horizontally is also one of the classic ways of generating more data for a classifier. For each image a horizontal and vertical flip is performed in the training set. Though natural images use horizontal flips, vertical flips capture a unique property of medical images, namely, invariance to vertical reflection. Conventionally, for natural images, only horizontal flips of the original images are used, since vertical flips often do not reflect natural images. However, a vertical flip of a mass would still result in a realistic mass.
2. Rotation augmentation are performed by the image rotation to right or left on an axis between 1° and 359°.
3. Brightness and Contrast adjustments are being done.

B. Annotation

3D Slicer is a open source tool for medical image computing. It is a software that provides versatile visualizations for radiology, programmed segmentation and registration for multiple applications. Advantages of 3D Slicer is it isn't specific to hardware, it facilitates translation and estimation of the new quantitative procedures for the implementation of the algorithm[12].

C. Segmentation

Image Data analysis can be done using multilayered artificial neural networks. The architecture of U-Net is developed on Fully Convolutional Network (FCN) having successive locally connected convolution, final upsampling layer and pooling layers. In contrary, the U-Net has symmetric downsampling and upsampling layers with deep skip connections; concatenation operator is applied to the skip connections between downsampling path and the upsampling path. Training examples were augmented and spatial transformations were used for the annotated samples to achieve good segmentation results[13].

Segmentation is the classification of each pixel. As such, early CNN segmentation models used small patches of the input image only to predict a single-pixel through a classification pipeline. Afterward, a full segmentation map was assembled using each of these pixels. This process was very slow, and it also prevented the network to have a field of view larger than the inserted patch. An improvement for segmentations came through architectures referred to as encoder-decoder models.

The encoding process describes the same spatial compression used in classification networks. Afterward, in the decoding step, the spatial resolution is brought back to its original shape and further processed by additional convolutions. This yields huge speed improvements, while also increasing the accuracy of the prediction.

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The number of parameters in a neural network has a high correlation with its learning capacity. By adding more nodes that can be adjusted during training, the model can approximate a more complex function that transforms the input into the output. The downside is that a larger parameter count will also increase the possibility of overfitting the data. A convention in the field of CNNs is to gradually increase the number of channels, while the spatial resolution is reduced due to the use of Max Pooling. U-Net also shows this behavior on the left side of its architecture.

D. Age Assessment

Patients who don't have legal certification determining their age is also a complex process. Natural process of bone formation is ossification, it is a unit of growth plates in the bone, which helps in assessing the bone. This approach enables the detection of bone structures.

IV. CONCLUSION

Due to lack in training data, Biomedical image segmentation is challenging. U-Net performance is good with lesser datasets that skip connections to combined features of low-level layers and high-level layers. Although U-Net has gained notable performance, it does not make use of the related information completely.

It can be stated that U-Net architecture only is not adequate to achieve precise segmentation. Shape information can be lost due to the fact that some lesions are minor that as the encoder decreases resolution, which delays the capability of the model to pick up complete lesion shapes. Therefore, we can increase the model by substituting the basic convolution blocks of the U-Net with dense blocks.

V. RESULTS AND DISCUSSION

Different classes have been developed to segment different cartilages of knee bone namely femur cartilage, patella cartilage and tibia cartilage as shown below, the model was trained to automatically segment them.

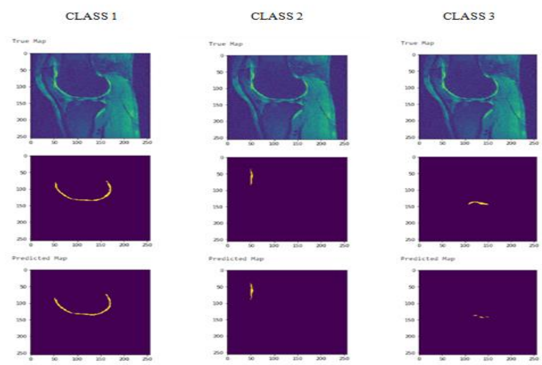

Fig 1. Different cartilages of knee bone.

Accuracy of the model is computed in Table 1.1. The Dice Similarity Coefficient (DSC) score is 98% and an Intersection-Over-Union (IoU) is 96%, this is given by the overlap area between the predicted segmentation and the ground truth divided by the union area of the predicted segmentation and the ground truth. This metric ranges from 0 to1 (0–100%) with 0 indicating no overlap and 1 indicating perfectly overlapping segmentation. Precision and Recall are balanced perfectly, demonstrating that predictions are neither too optimistic nor pessimistic. The error rate is 1.2%.

	DSC	IoU	Precision	Recall	Error
Merged	0.980	0.960	0.980	0.980	0.012
Femur	0.981	0.963	0.979	0.984	0.006
Tibia	0.977	0.955	0.976	0.977	0.006
Patella	0.953	0.911	0.954	0.952	0.001
Combined	0.979	0.958	0.977	0.981	0.004

Table 1.1 Evaluation result

The average success rate of the project was found to be 98% from table 1.1. The accuracy rate was dependent upon the model that is used.

The graph below shows the performance of the model during the segmentation of Femur, Tibia and Patella cartilages from the MRI of the knee.

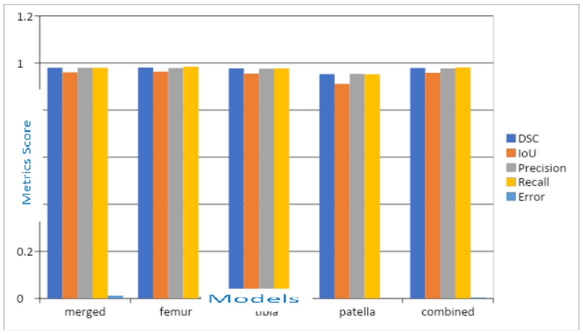

Fig 2: Visual representation of the evaluation result

The table 1.2 below gives the performance of the combined model on different sets over time on the training dataset, validation dataset and testing dataset.

Data	Epoch 1	Epoch 5	Epoch 10	Epoch 20	Epoch 40
Training Dataset	0.75	0.94	0.96	0.97	0.98
Validation Dataset	0.84	0.95	0.96	0.97	0.97
Test Dataset	-	-	-	-	0.98

Table 1.2: **Merged model Performance of the on different sets over time**

Validation data results never reaches 98% but final evaluation test set. Training data is slightly ahead of the validation results.

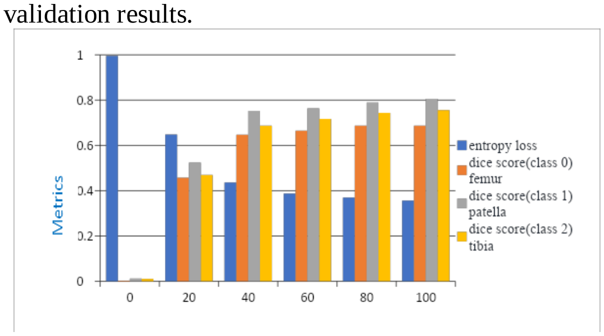

Figure 3: Evaluation metrics visual representation

The above graph shows the performance result of the U-Net model used in cartilage segmentation. In the above bar graph the first bar depicts the entropy loss which is used in measuring the performance of the model, here the value ranges from 0 to 1. Initially at epoch 0 the graph shows high loss as the model is not started to train. At later stages as the number of epochs increases, models will be trained with many images hence the loss value is decreased. At 100 epochs the final loss calculated is 0.356.

Epochs	Entropy Loss	Dice Score (Class0) Femur	Dice Score (Class 1) Patella	Dice Score (Class 2) Tibia
0	0.9958	0.0028	0.0122	0.0109
20	0.648	0.4578	0.5235	0.47
40	0.4366	0.6467	0.7529	0.6869
60	0.3876	0.6653	0.7632	0.7171
80	0.37	0.6876	0.7892	0.7441
100	0.3566	0.6867	0.8063	0.7558

Table 1.3 Cartilage Evaluation Result

The weighted cross entropy loss (CEL) could defined as:

Weighted-CEL $= -\frac{1}{N}\sum_{I=1}^{N}\sum_{j=1}^{4} wj(yijlog(pij))$

Where w_j = Weight of the jth segment. The weight can be calculated using many approaches that are based on the voxel count for that particular image/volume. N=number of voxels in the MRI volume or 2D MRI image, p_{ij} = probability of voxel i to be belonging to segment j, y_{ij} = label of voxel i to be belonging to segment j = 1 or 0.

The other metric used for measuring the quality of segmentation is dice score which is defined as:

Dice Score = $1-2\frac{\sum_{j=1}^{n4} wj\sum_{i=1}^{N} yijpij}{\sum_{j=1}^{4} wj\sum_{i=1}^{N} yij+pij}$

Here for each cartilage dice score is calculated separately. For femur dice score is 0.6867, 0.8063 for patella, and for tibia 0.7558.

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