Automatic Segmentation of Osteoarthritis using Cartilage in Knee Deep Learning Based Approach

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Abstract

Osteoarthritis (OA) is most typically a result of cartilage aging. Particularly in rural India, the percentage of people affected due to OA is far larger. It could be due to obesity, injuries or hereditary problems. This paper focuses on various aspects of severity analysis done using segmented cartilage. The automatic detection of OA severity supported by KL grades corresponding to several stages has been proposed by researchers and provides better results for analysis of the disease. Automatic segmentation approach using U-net, support vector machine-n classier is being implemented in this paper. The paper mainly focuses on all important issues related to segmentation in OA by testing on 100 images.

Keywords:_Segmentation, CNN, U-net, MRI, SVM, KL grading Classification._

1 INTRODUCTION

Knee osteoarthritis Analysis(OA) is the most prevalent cartilage articulation genes disorder in the world. OA results in persistent disability, early detection of OA is incredibly important nowadays. It affects an enormous number of elderly people due to ageing. Since the elderly the population would like to have a pain free active life, the diagnosis of OA has become a serious social and economic issue in health management. Average generation also gets affected due to an increasing obesity, making study of OA important. Osteoarthritis may damage ligaments, menisci, and muscles. Bone or cartilage fragments may degrade within the joint space, causing irritation and pain as shown in Figure 1. Hence early detection of cartilage deterioration is necessary. Osteophytes(cartilage degeneration leads to bony projection at joints), may develop, causing additional pain and doubtless damaging nearby tissues. According to a survey it is estimated 10%-15% of adults over 60 have some extent of osteoarthritis. OA commonly affects the joints within the knee, hands, feet, and spine, and is additionally common in other joints like the shoulder and hip joints. There are two sorts of OA: primary OA and secondary OA. Primary osteoarthritis could be due to many reasons like inflammatory, metabolic risks not only ‘wear and tear’ arthritis. Hence it is called a heterogeneous disease. Secondary OA is a pre-existing joint abnormality like trauma, injury such as sports injury, employment that needs kneeling or squatting for extended amounts of time, diabetes, or obesity. Though the aetiology is different than that of primary OA, the resulting symptoms and pathology are identical. Symptoms are pain, loss of ability, and joint stiffens after exercise or use. To assess the integrity of the cartilage, its biochemical composition must be measured. Several compositional Magnetic Resonance Image (MRI) techniques are introduced that are sensitive to either proteoglycan (delayed Gadolinium-enhanced MRI[dGEMRIC], Sodium-MRI, glycosominology chemical exchange saturation transfer [gagCEST]) or to a mixture of components (T2 time constant, time constant within the rotating frame [T1], magnetization transfer). Recently, DTI was introduced as a completely unique biomarker which will capture proteoglycan content and collagen structure simultaneously. Resonance imaging (MRI) methods are commonly used for clinical study of the structural changes within the articulation genes and, specifically, in articular cartilage. MRI systems provide highly precise images of tissue within the body. The systems detect and process the signals generated when hydrogen atoms, which are abundant in tissue, are placed in an exceedingly flux and excited by a resonant magnetic excitation pulse. Hydrogen atoms have an inherent torque as a result of their nuclear spin. When placed in an exceedingly strong flux, the magnetic moments of those hydrogen tend to align. Superficially, one can consider the hydrogen nuclei in an exceedingly static flux as an elastic string under tension. The nuclei have a Larmor frequency determined by their localized flux strength, even as a string contains a resonant frequency determined by the strain thereon. For hydrogen nuclei in an exceedingly typical 1.5T MRI field, the resonant frequency is approximately 64MHz. To measure MRI parameters in cartilage, the cartilage has to be annotated and segmented, which is sometimes done by an expert or a trained Radiologist which takes few hours to finish segmenting all cartilage plates (tibia, femur, patella) from a patient's MRI. This fashion of segmentation isn't adaptable and intensely slow. Deep learning-based models are successful in performing quick and accurate segmentation of brain, tumour, pancreas, cardiac substructures and other biological parts. Here, we imply to use deep learning methods to automate the segmentation of knee cartilages.

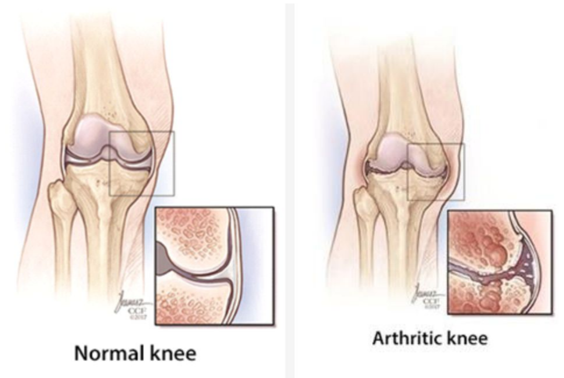

Figure1: Normal Knee vs OsteoArthritis Knee

2 LITERATURE REVIEW

Yaodong Du et al.[1], demonstrate OA using CDI(Cartilage Damage Index) and KL grading technique using machine learning techniques like Artificial neural network (ANN), which showed good performance. For KL grade classification, experiment results showed that adding patella points improved the performance remarkably, from AUC 0.822 to AUC 0.903 and also the entire knee CDI achieved the foremost effective classification performance on the dataset. Egor Panflov[2], investigated two modern regularization techniques- mixup and adversarial unsupervised domain adaptation (UDA)-to boost the robustness of DL-based knee cartilage segmentation to new MRI acquisition settings. And their validation setup included two datasets produced by different MRI scanners and using distinct data acquisition protocols. They achieved an honest performance. Alejandra Duarte demonstrates the manual segmentation is error-prone and time-consuming (few hours per subject). they use an ensemble of modified U-Nets to automate this segmentation task. They benchmark their model against somebody's expert test-retest segmentation and conclude that their model is superior for Patellar and Tibial cartilage using dice score as the comparison metric. In the end, they are doing a perturbation analysis to know the sensitivity of their model to the various components of their dataset. They also provide confidence maps for the predictions for radiologists to use the model predictions analysis[3]. Yaodong Du and Juan Shan[4], explored the hidden biomedical information from knee MR images for OA prediction. They have computed the Cartilage Damage Index (CDI) information from 36 informative locations on tibiofemoral compartment from 3D MR imaging reconstruction and used PCA analysis to process the feature set. The processed feature set and original raw feature set were served as input to four machine learning methods (artificial neural network (ANN), support vector machine (SVM), random forest and naive Bayes) respectively. to look at the various effects of medial and lateral informative locations, they need to divide the 36-dimensional feature set into 18-dimensional medial feature set and 18-dimensional lateral feature set and run the experiment on four classifiers separately. Experiment results showed that the medial feature set generated better prediction performance than the lateral feature set, while using the entire 36-dimensional feature set generated the simplest. PCA analysis is useful in feature space reduction and performance improvement. The simplest performance was achieved by ANN with area under the receiver operating characteristic (ROC) curve = 0.761 and F-measure =0.714. Sharma M.K. et al.[5] determines that there's no artificial material that may replace only the cartilage at the joint. In a clinical assessment study conducted on Indian population consisting of 362 elderly of over 65 years, osteoarthritis was present in mere 50.2% of the elderly aged 65-74 years, whereas it had been 97.7% in elderly aged 84 years and above. Stefan M. et al. proposed that the presence of osteophytes within the patella femoral compartment is additionally related to pain. All other abnormalities in cartilage, menisci and subchondral cysts will be found in MR imaging only. The utilization of MRI for diagnosis and assessment of cartilage defect repairs has been studied[6]. The development of 2-D active contour algorithm, by Claude[7] provides a neighbourhood frame of reference (LCS) is developed for the femoral and tibial cartilage boundaries for the measurement of thickness and volume. Snoeckx A. et al.[8] claims cartilage lesions, bone marrow edema pattern and meniscal lesions are well detected on MR Images in patients with advanced OA. Anatomical variants within the knee are frequent findings on MRI. Thorough knowledge and familiarity with variants and its pathological nature are important for accurate interpretation of imaging studies. Demonstration of an interpolated cubic B-spline curve by Zohara et al.[9] develops a semiautomatic method, initially cartilage is segmented manually by marking the consecutive points along the articular contour curves with a typical spacing of 0.5-1.0 mm. Peter

R.K. et al.[10] proposed quantification of cartilage thickness, volume and progressive assessments image processing techniques are used. Association between clinical features and MR image findings of diglymes are evaluated and it's found that an outsized joint effusion is related to pain and stiffness. Alireza Norouzi et al. [11] have described the newest segmentation techniques useful in medical image analysis. Methods discussed are classified into 4 classes; region-based methods, clustering, classifiers and hybrid methods. They concluded that the thresholding and region growing approaches are simple to implement but are sensitive to noise whereas clustering and classification approaches have time complexities that are difficult to implement. Lastly, they also presumed that hybrid approach obtained optimum results with reasonable accuracy.

3 METHODOLOGY

3.1 DATASET

3.1.1 DATA SOURCE AND DESCRIPTION

Each diffusion MRI includes 15 spatial 256*256 images with a resolution of 0.6*0.6*3 mm3 covering the entire knee. Every image is obtained 7 times with different diffusion directions and orientations.Each diffusion-weighted dataset is a 256 *256 *7 *15 matrices associated with an individual patient. A musculoskeletal radiologist has segmented all cartilage plates (lateral and medial tibia, femur and patella) in each diffusion weighted acquisition in the form of a binary mask. These will be considered as the ground truth. A sample image is shown below. In addition to the 7 contrast (diffusion direction and orientation) images, we have also used additional two maps which were calculated using the 7 contrast images. These maps are referred to as the mean expansion maps and fractional dimension maps. These maps help a radiologist distinguish between articular cartilage and fluid. Since fluid and articular cartilage have similar voxel intensity.

3.1.2 TRAIN - VALIDATION – TEST SPLIT

Among the 71 MRI volumes, there could be several volumes for one particular patient but these volumes are obtained over a certain period of time. Therefore, while splitting the data, it has to be ensured that each patient and all the MRI volumes belonging to them should be in one particular set. The training set contains 57 MRI volumes, while the validation and testing set had 7 MRI volumes each.

3.1.3 DATA PREPROCESSING

Our models used 15 spatial images as a separate 2D image with nine channels. Nine channels include the seven contrast images, one mean expansion map and one fractional dimensional map. Therefore, the 3D MRI volume of 256 *256*9*15 were split into 15 2D images of size 256*256*9. Pre-processing for 2D MRI image: The values in each channel of the 2D MRI image was normalized to be between 0 and 1 using the min-max normalization method. The least and greatest voxel intensity was taken across that particular channel of that particular image for which the normalization was supposed to be done. Converting Image into Patches: For the purpose of training a classifier which is not convolutional (SVM or Random Forest), we convert one image into several 15 *15 patches which are extracted with a stride of 1. The exact way in which this patch is used is discussed in the modelling section. For the purpose of training our convolutional neural networks, we extract 50*50 patches with a stride of 15. We note that, theoretically, training on patches is equivalent to training on the whole image due to the spatial invariance underlying convolution. In addition to this, training on patches provides us with the advantage of using a larger batch size as more samples can fit into the GPU and also doing much more gradient updates in just one batch as the patches are overlapping.

3.2 DEEP CNN MODELS

We trained a deep convolutional neural network which consisted of 3x3 convolution kernels, followed by a Relu and batch norm which was repeated 17 times. This model wasn't performing very well and this led us to believe that a multi resolution approach is necessary. A recent approach towards building deep learning models for segmentation is the fully convolution encoder-decoder approach. The encoder encodes the high-resolution input to a low-resolution output and a decoder decodes this low-resolution output back to high-resolution output. The up sampling and down-sampling are done using stride transposed Convolutions. The low-resolution output efficiently captures the high-level class specific features whereas the high-resolution input captures the low-level semantics like edges, corners, spatial information etc. Therefore, while reconstructing the segmentation maps, the low-level semantics which gives spatial information and the high-level class specific features which recognizes the object class are important. We, therefore, use the skip connections that help us to directly connect high-resolution inputs with high-resolution decoded outputs. This is a basic structure of many state-of-the-art segmentation models like U-Net and RefineNet . We try a basic U-Net type of architecture and many improvements over it are tried to get better dice scores. The details of different architectures are described below(Figure 2).

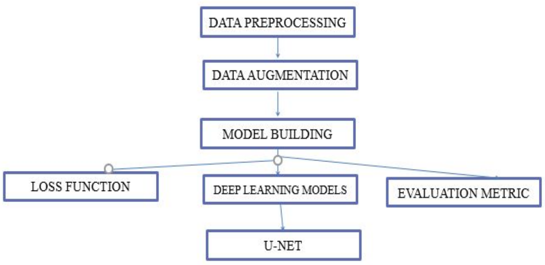

Figure 2: The methodology of proposed system.

3.2.1 U-NET

A Baseline U-Net model was built for 2D images. The architecture is seen within figure 3. The baseline U-Net model for 2D images had 9.8 million learn-able parameters. The prediction was done by taking an argmax on the probability maps across 4 segments. In other words, the probability for every voxel belonging to 4 classes are calculated and the voxel is assigned to class with highest probability.

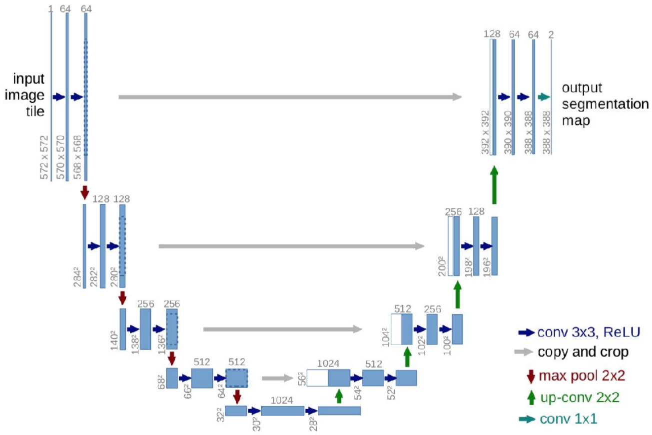

Figure 3: The architecture of U-net

The small print of the training procedure and performance is discussed in the results section. For segmentation we first preprocessed the data using the coronal view. and we annotated the image from that data whatever we have got the image that we train using the U-net model where we calculate the dice score of the image after segmentation. hence we can prove the U-net model gives the best dice-score compared to other models.

3.2.2 Support Vector Machine(SVM)

Artificial Neural Networks perform well in many image processing applications like coding, pattern recognition and texture segmentation. Support Vector Machines is one in every of the foremost recent ideas in artificial Neural Networks. This new learning algorithm was proposed by V. Vapnik and relies on Statistical Learning Theory. The Support Vector Machine implements the subsequent idea: it maps the input vector x into a high-dimensional feature space Z through some nonlinear mapping, chosen a priori. During this space, an optimal separating hyperplane is constructed". Within the case of pattern recognition, SVMs perform classification between two-point classes by finding a call surface determined by certain points of the training set, termed Support Vectors. In the pattern recognition field the SVM have already been used for handwritten digit recognition, beholding, identification, face detection in images and text categorization. Another important characteristic of SVM is that while most classical neural network algorithms require a billboard ad hoc choice of the system's generalization ability, the SVM approach proposes a learning algorithm to regulate the generalization ability of the system automatically.

4 RESULTS

We trained the models to classify the severity of knee osteoarthritis using KL-grading. Figure 4 and 5 shows the implementation results. from which we can tell that classification using svm is more accurate than the knn classifier where the svm gives an accuracy of 0.73 whereas knn gives a accuracy of 0.705.

```
Best Hyper Parameters: {'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_state': 123}
[[151  35]
 [ 23  15]]
              precision    recall  f1-score   support

           0       0.87      0.81      0.84       186
           1       0.30      0.39      0.34        38

    accuracy                           0.74       224
   macro avg       0.58      0.60      0.59       224
weighted avg       0.77      0.74      0.75       224

Accuracy: 0.7410714285714286
```

```
Best Hyper Parameters:
 {'algorithm': 'auto', 'leaf_size': 1, 'n_jobs': -1, 'n_neighbors': 9, 'weights': 'distance'}
[[130  56]
 [ 17  21]]
              precision    recall  f1-score   support

           0       0.88      0.70      0.78       186
           1       0.27      0.55      0.37        38

    accuracy                           0.67       224
   macro avg       0.58      0.63      0.57       224
weighted avg       0.78      0.67      0.71       224

Accuracy: 0.6741071428571429
```

Figure 4: Output using Dsc

Figure 5: Output using KNN

```
Best Hyper Parameters:
 {'criterion': 'gini', 'min_samples_leaf': 1, 'min_samples_split': 3, 'n_estimators': 25, 'n_jobs': -1, 'random_state': 123}
[[149  37]
 [ 23  15]]
              precision    recall  f1-score   support

           0       0.87      0.80      0.83       186
           1       0.29      0.39      0.33        38

    accuracy                           0.73       224
   macro avg       0.58      0.60      0.58       224
weighted avg       0.77      0.73      0.75       224

Accuracy: 0.7321428571428571
```

```
Best Hyper Parameters:
 {'C': 10000, 'kernel': 'rbf'}
[[149  37]
 [ 23  15]]
              precision    recall  f1-score   support

           0       0.87      0.80      0.83       186
           1       0.29      0.39      0.33        38

    accuracy                           0.73       224
   macro avg       0.58      0.60      0.58       224
weighted avg       0.77      0.73      0.75       224

Accuracy: 0.7321428571428571
```

Figure 6: Output using random forest

Figure 7: Output using SVM

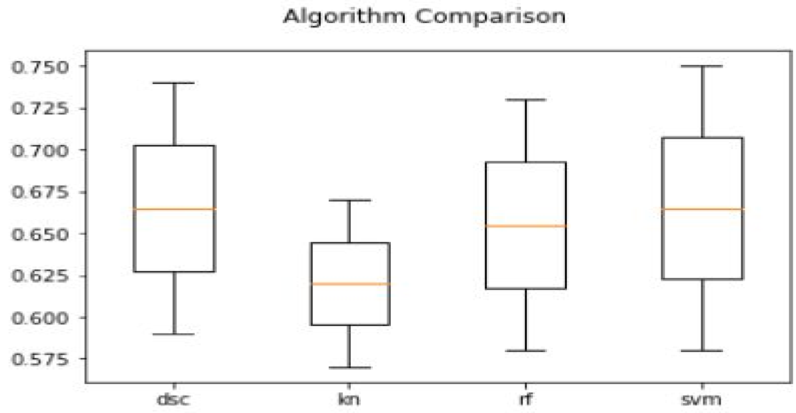

Figure 8: algorithm comparison

5 FUTURE WORK

As discussed above, if the dataset is acquired from multiple radiologists the matter of noisy ground truth is often resolved. Another approach is often to coach models using label smoothing. As a future work, we'd wish to optimally train the model using label smoothing and also simultaneously gather data from multiple radiologists.

6 CONCLUSION

In this paper, we have used the U-net model for segmenting the cartilage and few deep learning algorithms such as SVM, KNN for classification of OA severity. The segmentation was carried using the U-net model of CNN, where segmentations of the test set are very accurate, the average DICE coefficient is 0.98. We used a .csv file for training the SVM model to perform classification. We checked for 1000 weights and we identified grade 0-186, grade 1-38,we can conclude SVM provides accurate results than other algorithms.

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