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Machine learning techniques for Quantification of Knee Bone Segmentation and detection of Osteoarthritis severity from MR Images

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Abstract:

In this modern era, several technologies have been developed for medical image processing. Magnetic resonance imaging (MRI) is precise and efficient for interpreting the soft and hard tissues. In this project, we want to detect and classify Osteoarthritis in the knee from medical images using Deep Features to categorize the images. This paper presents a technique for knee MRI segmentation using dual channel U-net architecture(DC-UNet) followed by classification of the severity of knee osteoarthritis using the ResNet 152V2 model of the Keras applications library. In this project, the problem of noises and lack of dataset can impact on the detection and classification of target areas in images and because of it the irrelevant features could be selected from the medical images. The model is implemented by using two separate neural networks serially connected for detection and classification of osteoarthritis. The models are trained with 101 MR images and tested with 32 MR images. The model presented in this paper uses data to segment the knee bone after data augmentation, with the architecture of the dual channel UNet. The model performs with a dice score of 0.80 and the classification accuracy of 76.67.

KeyWords: Magnetic resonance,segmentation, Convolutional Neural Net, Femur, Tibia.

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I. INTRODUCTION

Knee joint is the largest complex joint in the body. Osteoarthritis is a leading cause of disability in older adults.Osteoarthritis is seen when the cartilage becomes soft and gets eroded due to continuous wear and tear because of aging. This causes inflammation and decrease in movement of joints leading to formation of new bone spurs(tiny growths of new bone). Severity of OA is graded based on clinical examination, symptoms and simple radiographic assessment techniques (X-ray), MRI, CT in most cases. MR imaging has the ability to cover the whole knee during examination. MRI images are widely used for diagnosis of knee joint abnormalities. This imaging modality can be used in in-vivo and in-vitro studies of anatomical structures. The progression of OA is very often slow and it can take many years before the cartilage is reduced from its typical thickness of a few millimeters to possible total loss.

This paper introduces a segmentation model which inturn leads to the classification pipeline to finally detect the severity of knee osteoarthritis. The criteria used for classification is the KL grading. The KL

grading system or the Kellgren and Lawrence system is the most commonly used method of differentiating the severity of osteoarthritis (OA) using a scale of 5 grades. The grades range from grade 0 to grade 4 with a description that is 0-None,1-Doubtful, 2-Minimal, 3-Moderate, 4 -Severe. Fig 1.1 describes the exact differentiation between the grades that are used to classify the severity.

The dataset consists of MRI images and is collected by a local radiology department in our city. We used the sagittal view of the Magnetic Resonance images as they are the most widely considered to diagnose and categorise osteoarthritis. The MR images were annotated and verified by the radiologist.

KL Grade	Description
0	No radiographic features of osteoarthritis
1	Doubtful joint space narrowing and possible osteophytic lipping
2	Definite osteophytes and possible joint space narrowing
3	Multiple osteophytes, definite joint space narrowing, sclerosis, possible bony deformity
4	Large osteophytes, marked narrowing of joint space, severe sclerosis, and definite deformity of bone ends

Fig. 1. KL Grades

The existing systems require a huge amount of dataset requirement for effective learning. There are also traditional segmentation algorithms but do not give us the desired result in the case of medical images. The use of data augmentation was not used in earlier systems as there was no scarcity of dataset. This proposed system allows the model to segment bones with very less annotated images and hence could be significantly useful in the field of medical science.

1. PROPOSED SYSTEM

Here, in this section several phases to segment and classify osteoarthritis severity is discussed.The complete procedure has been divided into different steps and the same are discussed here. The images were first collected by a local radiologist and were annotated manually. The annotation includes the labelling and masking of the femur and the tibia. Due to the scarcity of training data, our segmentation model is based on the DC-UNet architecture with images being augmented so as to prevent our model from overfitting.

Then the images are passed into the classification model i.e ResNet152 V2 to further train the model to classify the images into their KL grades. KL grades in our case are represented by four instead of five levels as follows. 0-Normal,1-Mild,2-Moderate,3/4 -Severe. The pipeline is then evaluated with the dice score for segmentation and validation accuracy for classification. The models were then tested individually and then in a pipeline to complete our overall process for segmentation and classification. Figure 2a represents a pipeline of our process that is used for execution. Each phase of our model was divided into a sequence of steps and the same are discussed below.

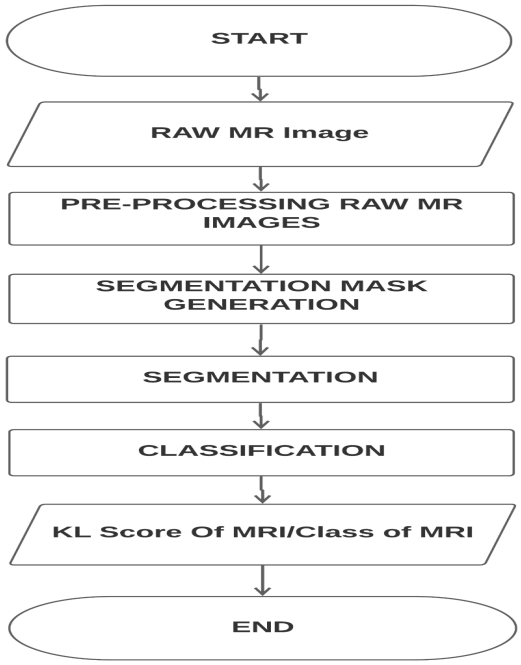

Fig. 2. System Flowchart

Figure 2.1 represents a pipeline of our process that is used for execution.

2.1 IMAGE ACQUISITION AND MASK GENERATION

Initially raw MR images of the sagittal view of osteoarthritis affected patients were collected from a local radiological department. All the images collected were previously classified into the KL score. The images were then preprocessed to feed it into our model.

First, the images were cropped into the size of 400 x 400 to remove unnecessary parts, resized to 384X384 to suit the DC Unet architecture requirements and then annotated. The images were also converted into grayscale since the single channel color would reduce significant training time for the models. Annotations here are labeling the image and generating segmentation masks which are also fed into the network for training.

The images were labeled in an open source software Labelbox. The objects that were annotated were the femur (thigh bone) and the tibia (shinbone) which were then later exported. The exported objects were then generated into a binary mask image. The binary mask image and the original image would act as the ground truth to train our segmentation model. Fig 3(a) represents an osteoarthritis affected knee and Fig 3(b) represents its corresponding segmentation map (mask) .

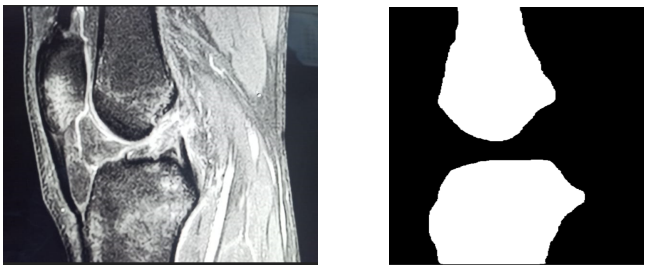

Fig. 3(a). Preprocessed Image and 3(b) Segmentation Mask

2.2 IMAGE SEGMENTATION

Here in this section, the segmentation model used is discussed with actual hyper-parameters used to build our sequential Neural-network model.

CNN has been a huge leap for medical image segmentation.One of the most widely used approaches to medical image segmentation tasks is Unet. However, it is also true that the Ronneberger's U-Net architecture has limitations in several aspects.

The modifications applied to the U-net architecture were : 1) Encoder and Decoder was replaced with newly designed efficient CNN architecture , 2) To replace skip connection between encoder and decoder to improve based on the-state-of-the-art U-Net model residual module was applied. This applied modification has improved the performance of the Dual-Channel-UNet compared to the earlier UNet versions.

Table 2.1 shows the various hyperparameters of the DC-Unet.

DC-UNet							
Block	Layer (left)	#Filters	Layer (right)	#Filters	Path	Layer	#Filters
DC Block 1 DC Block 9	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	8 17 26	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	8 17 26	Res Path 1	Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1)	32 32 32 32 32 32 32 32
DC Block 2 DC Block 8	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	17 35 53	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	17 35 53			
DC Block 3 DC Block 7	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	35 71 106	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	35 71 106	Res Path 2	Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1)	64 64 64 64 64 64
DC Block 4 DC Block 6	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	71 142 213	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	71 142 213	Res Path 3	Conv2D(3,3) Conv2D(1,1) Conv2D(3,3) Conv2D(1,1)	128 128 128 128
DC Block 5	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	142 284 427	Conv2D(3,3) Conv2D(3,3) Conv2D(3,3)	142 284 427	Res Path 4	Conv2D(3,3) Conv2D(1,1)	256 256

Table. I. Internal Architecture of Dual Channel Unet

The UNet is an amazing and the most popularly approved architecture in medical image segmentation. However it does not perform well in challenging medical images cases such as noisy objects and interference of backgrounds and overlap of borders. To solve images having small bordered objects ,spatial features are utmost important. Therefore,to overcome the problem of lack of spatial features, a sequence of three 3 × 3 conv layers were used to change the residual connection in the Multi-Res(modified UNet for different scale features) block called the Dual Channel Block.

Every channel in the DualChannel block has exactly half filter numbers of the Multi-Res block :[32, 64, 128, 256, 512] And, the quantity of filters in Residual-path are [32, 64, 128, 256] respectively and the number of each layers' filter is shown in Table 1. Every conv layer in the DualChannel-UNet is activated by the Rectified Linear Unit(ReLU) function. Batch normalization is used to avoid overfitting. The last output layer is activated by the sigmoid activation function.The models were trained using the Adam optimizer.

Consider every input image as X,assuming the prediction of model output is $\hat{y}$ and the ground truth is y. Hence, the binary cross-entropy is given as:

$$\textit{Cross Entropy}(y, \hat{y}) = \sum_{x \in X} -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y}))$$

Loss function j for a batch of n images is give as:

$$J = 1/n \sum^{n}_{=1} \textit{Cross Entropy}(y, \hat{y})$$

2.3 IMAGE CLASSIFICATION

Here in this segment,the classification model used is discussed with the actual parameters used for the multi-class classification in this case.The model being used is a Version 2 of resnet with 152 layers. To develop this model we use keras applications library which consists of various versions of resnet architecture.

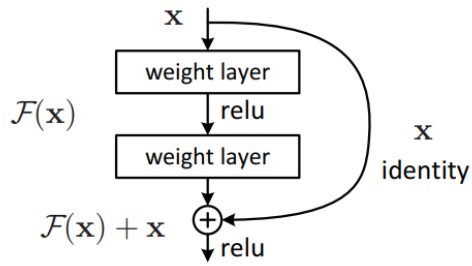

Figure. 4. Residual Block

Microsoft Research came up with a new architecture called ResNet in short for Residual Network in which to overcome the problem of vanishing/exploding gradients in deep neural networks a concept of Residual blocks was used.Residual block consists of skip connections that skip the training from few underperforming layers or some layers that can harm the performance of the entire network.

Before multiplying input to the weight matrix(conv operation) Residual Network Version-2(V2) applies Batch-Normalization & ReLU activation function on input. i.e, V2 performs preactivation instead of post activation used in V1.The output of the addition operation between the identity mapping and the residual mapping should be provided as is to the next block for further operations, according to ResidualNetwork-Version-2. If the function 'f' is an identity function, the signal will be transferred directly between any two units. As a result, the gradient value calculated by the output layer will readily reach the starting layers even if the signal does not change.

The model uses manually generated segmentation masks of size 384X384 as input for training.The input is augmented using various parameters so as to increase the data by some folds.The augmentations applied include zoom, shear, vertical and horizontal flips ,rotations,vertical and horizontal shifts and some brightness changes.Data then flows through multiple residual blocks of the network.Each block consists of combination of zero or more convolutional layers and pooling layers.First block consists of conv layer with patch size 7X7 with stride 2,followed by pooling layer with patch size 3X3,stride 2.Blocks that follow have filters ranging from of 1X1,64 , 1X1,2048 ,3X3,64,3X3,512.Input Image undergoes convolution operations, pooling and reshaping to finally arrive at the categorical output. Trained model uses the output of the Segmentation model as input to give one of the four classes as final output.This output can be mapped to KL grades as mentioned above.

2. RESULTS AND DISCUSSION

For the experimental results, we acquired our own dataset consisting of 101 training images and 32 images for testing. The dataset was preprocessed and fed into the segmentation and classification models for training

The evaluation metric used for the segmentation model was the dice coefficient. Simply expressed, the dice coefficient is equal to twice the overlapped area divided by the total number of pixels in both images.

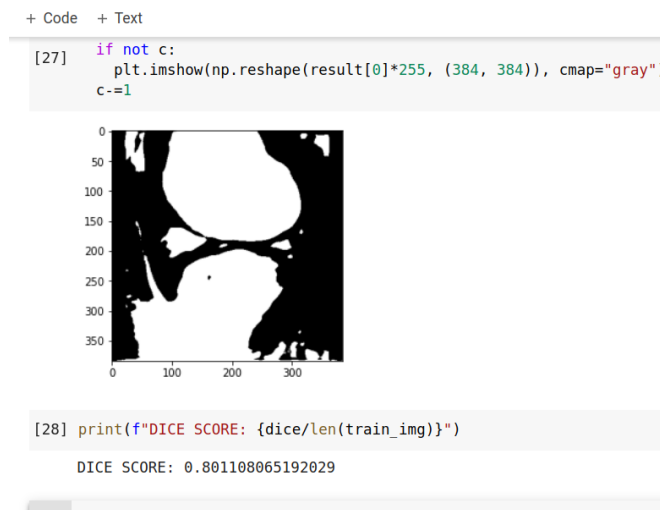

Figure.5. Segmentation Dice Score

Another simple way of evaluating the segmentation is by pixel error.Pixel error is calculated by measuring the pixel difference between labeled images and segmented images.Unet Pixel error is 0.0611 which is comparatively higher compared to Pixel Error: 0.018451793411335474 of DC-Unet.

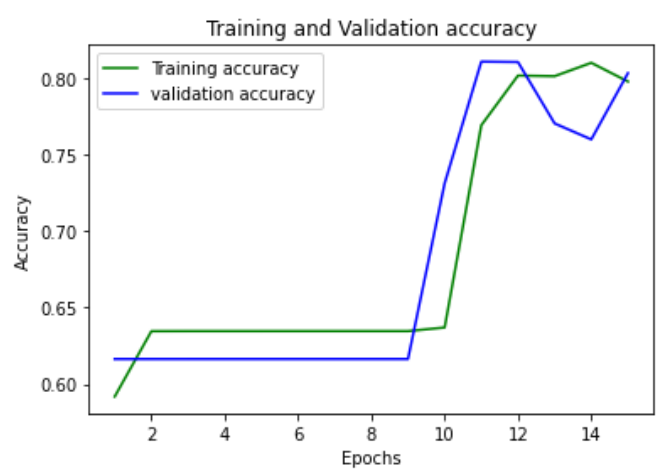

Figure.6. Training v/s validation accuracy

Figure.7. Training vs Validation loss

The classification model used validation accuracy for its evaluation. The dice coefficient observed for the segmentation was 0.80 while the validation accuracy was 76.67%. Classification Precision value was found to be 0.5204.This may be due to the imbalance of classes in the dataset.

3. CONCLUSION

In this paper, we have developed a model to detect knee bones in a MR image thereby reducing the non-essential features and allowing the classification model to extract features from a segmented image. Since KL score is based on the relative space between the femur and tibia. . We have made sure that the approach will give best results in Realtime and provide a research base to other researchers to carry further work in the field of medical Image Processing and Deep Learning.The paper tries to come up with a system for detecting Knee Osteoarthritis and then classify Osteoarthritis based on severity to hopefully help faster and easier medical diagnosis, after some improvements.

Due to a lack of data as well as a lack of time,various adjustments, testing, and experiments have been postponed for the future. To obtain higher precision, the trials necessitate a significant amount of data. Experiments using real data are also typically very consuming, taking days to complete a single run. Future work for this research will focus on resolving the KOA detection and classification challenge while taking into account additional OA case possibilities such as edoema and osteophytes. The project's future scope would include using a big dataset of OA knee MRIs and working on additional two perspectives such as axial and coronal.This would aid this effort in categorizing and detecting disease sites, even in small OA instances, with more precision. Other future scopes would involve experiments on 3-D pictures, which could aid in detecting the presence of disease regions across the knee. Another future scope for this study would be to work on the medical pictures of other body joints also. After completing so much work on this project, the model would be able to predict cases of OA as well as determine the cause of OA presence in a patient's knee as well as other body joints.

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