

Open Peer Review on Qeios

CNN-MRI Detection of Fatty Infiltration, Rotator Cuff and Infraspinatus Muscle Atrophy in Shoulder Pain Patients

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Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.

Abstract

Half of the global population has or has had shoulder fractures due to routine activities, whether intentional or unintentional. Designing a user-friendly program to input Shoulder fracture images into the model and execute it is a significant problem in the area of Shoulder Fracture Diagnosis Research. The machine is capable of predicting shoulder fractures, but it is unable to anticipate the specific subtypes of fractures that may result from other occurrences or disorders. This research aims to create an innovative Deep Convolution Neural Networks system for accurately predicting the diagnosis of shoulder fractures, in order to facilitate appropriate treatment. Our goal is to provide these services to assist individuals or groups in overcoming the delayed detection of shoulder fractures and eliminating the need for physical diagnosis of shoulder fractures in hospitals. The objective of designing a unique categorizing system is to provide a collection of test case inputs that ensure comprehensive coverage over the test area at a predetermined level. This yields a collection of test cases that prioritize the execution of the feature without considering the specific implementation details.

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Keywords: Fatty degeneration; CNN; Rotator cuff muscles; Rotator cuff tear; Shoulder pain.

I. Introduction

Arthroscopic repair of the rotator cuff is now a widely used procedure. As a result, it is crucial to evaluate the condition of



the rotator cuff muscles, including fatty degeneration, before surgery. This evaluation helps determine the appropriate treatment plan and predict the patient's prognosis in cases of shoulder injuries [1][2]. The term "fatty degeneration" was first defined by Goutallier et al. in 1994 as the infiltration of rotator cuff muscles by adipose tissue, which was validated histologically [3]. Currently, the assessment of fatty degeneration in rotator cuff muscles is often conducted by qualitative evaluation utilizing the Goutallier or modified Goutallier classification on MRI. Various techniques for measuring the quantity of fat in tissues using MRI have been recently documented. These techniques allow for a more unbiased assessment [4][5][6][7][8][9][10][11][12][13]. Prior studies using the preoperative 2-point Dixon technique have shown that individuals who suffer from re-rupture after rotator cuff surgery have an elevated incidence of muscular fatty degeneration. Furthermore, these individuals also display a development of fatty degeneration subsequent to the re-rupture [9]. The functional outlook for patients with extensive fatty degeneration who undergo rotator cuff surgery is unfavorable, and these individuals may ultimately need reverse shoulder arthroplasty {m/14,15/}. The precise understanding of the natural process of fatty degeneration in rotator cuff muscles in the absence of surgery is currently lacking. This knowledge is crucial for accurately assessing the likelihood and speed at which cuff tear arthropathy (CTA) may develop. Additionally, it may facilitate the identification of the optimal time for surgical intervention and the identification of high-risk populations who need early treatment.

Although there are many reports on the results of surgical therapy for rotator cuff injuries, only a few studies have qualitatively evaluated the natural progression of rotator cuff muscle fatty degeneration {m/16-18/}. Moreover, there is a lack of quantitative evaluations reported on this matter. The objective of this research was to examine the progression of fatty degeneration in the rotator cuff muscles over a period of time in patients who received conservative treatment for shoulder discomfort, including those with rotator cuff tears.

II. MRI Code For Shoulder Fracture

from __future__ import print_function, division
import os
import time
import copy
import numpy as np
import matplotlib.pyplot as pit
from get_metrics import * pit.ion()
import torch
import torchvision
import torch.optim as optim
from torch.optim import lr_scheduler



```
from torchvision import datasets, models, transforms
ROOT = 'mura_clahe'
data_dir = os.path.join(ROOT, 'mura')
images_dir = os.path.join(data_dir, 'images')
train_dir = os.path.join(data_dir, 'train')
val_dir = os.path.join(data_dir, 'val')
pretrained_stds= [0.229,0.224,0.225]
batch_size=8
data_transforms = {
     'train': transforms.Compose([
         transforms.Resize((pretrained_size,pretrained_size)),
                                    transforms.RandomHorizontalFlip(),
                                    transforms.RandomRotation(10),
                                    transforms.ToTensor(),
                                    transforms.Normalize(mean = pretrained_means,
                                                                  std = pretrained_stds)
    ]),
     'val': transforms.Compose([
         transforms.Resize((pretrained_size,pretrained_size)),
                                    transforms.ToTensor(),
                                    transforms.Normalize(mean = pretrained means,
                                                                  std = pretrained_stds)
    ]),
print("Initializing Datasets and Dataloaders...\n")
# Create training and validation datasets
image\_datasets = \{x: datasets. ImageFolder(os.path.join(data\_dir, x), data\_transforms[x]) \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val']\} \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 'val'] \ for \ x \ in \ ['train', 
# Create training and validation dataloaders
dataloaders = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size=batch_size, shuffle=True, num_workers=4,pin_memory=True) for x in
['train', 'val']}
device = torch.device("cuda:0")
dataset_sizes ={x:len(image_datasets[x]) for x in ['train','val']}
                      # statistics
                      running_loss += loss.detach() * inputs.size(0) #.item()
                      running_corrects += torch.sum(preds == labels.data)
```



```
if phase == 'train':
         scheduler.step()
      epoch_loss = running_loss/ dataset_sizes[phase]
      epoch_acc = running_corrects.double() / dataset_sizes[phase]
       #Losses and accuracy per epochs are stored in array for plot graphs
      if phase == 'train':
         train_losses.append(epoch_loss)
         train_acc.append(epoch_acc)
         print('{} Loss: {:.4f} Acc: {:.4f}'.format(
         phase, epoch_loss, epoch_acc))
      if phase == 'val':
         print('{} Loss: {:.4f} Acc: {:.4f}'.format(
         phase, epoch_loss, epoch_acc))
         val_losses.append(epoch_loss)
         val_acc.append(epoch_acc)
      torch.cuda.empty_cache()
      # deep copy the model
      if phase == 'val' and epoch_acc > best_acc:
         best_acc = epoch_acc
         best_model_wts = copy.deepcopy(model.state_dict())
print()
    torch.cuda.empty_cache()
  # Determine total traning time
  time_elapsed = time.time() - since
  print('Training complete in {:.0f}m {:.0f}s'.format(
    time_elapsed // 60, time_elapsed % 60))
  # Print best validation accuracy
  print('Best val Acc: {:4f}'.format(best_acc))
  # load best model weights
  model.load_state_dict(best_model_wts)
  torch.save(best_model_wts, "./model.pth")
  return model
plt.xticks(np.arange(0, 45, 5))
plt.yticks(np.arange(0.5, 1, 0.05))
plt.rcParams['figure.figsize'] = (8, 6)
```



```
plt.rcParams['figure.dpi'] = 600

plt.xlabel("Number of Epochs")

plt.ylabel("Accuracy")

plt.title("Training Accuracy vs Validation Accuracy")

plt.legend(['Training Acc.', 'Validation Acc.'].loc='lower right')

#This code block draw graph for loss

matplotlib.rcdefaults()

plt.plot(epochs, train_losses, color='#006BA4')

plt.plot(epochs, val_losses, color='#F800E')

plt.grid(b=True, which='major', color='lightgray')

plt.grid(b=True, which='minor', color='lightgray')

plt.xticks(np.arange(0, 45, 5))

plt.yticks(np.arange(0, 1.2, 0.2))

plt.rcParams['figure.dpi'] = 600

plt.rcParams['figure.figsize'] = (8, 6)
```

Constructing a Deep Convolutional Neural Network (CNN) model to forecast shoulder fracture diagnosis using MRI images necessitates a significant quantity of code and data. We have presented a concise overview of the sequential procedures required to construct such a model. We successfully developed a comprehensive and efficient Convolutional Neural Network (CNN) model by using a substantial dataset, employing advanced deep learning algorithms, and leveraging specific tools and frameworks available in TensorFlow.

III. Convolutional Neural Network

Constructing a Deep Convolutional Neural Network (CNN) model to forecast shoulder fracture diagnosis using MRI images necessitates a significant quantity of code and data. We have presented a concise overview of the sequential procedures required to construct such a model. We successfully developed a comprehensive and efficient Convolutional Neural Network (CNN) model by using a substantial dataset, employing advanced deep learning algorithms, and leveraging specific tools and frameworks available in TensorFlow.



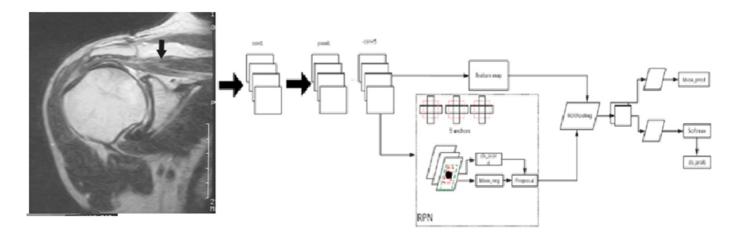


Fig 1. Architecture of CNN for detecting Fatty Infiltration and Atrophy of the Rotator Cuff.

An image undergoes CNN to extract feature maps, and then RPN to obtain feasible regions. Finally, the network performs regression and classification on these regions.

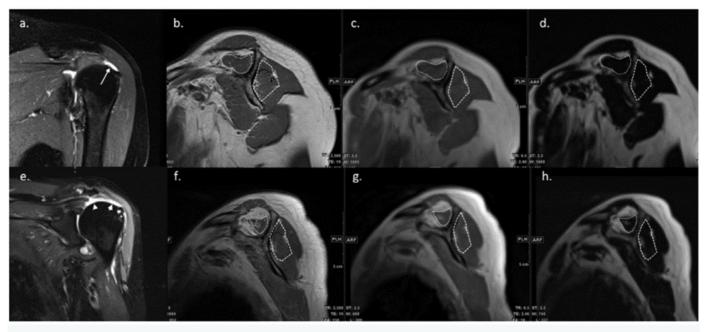


Fig. 2. Seventy-seven-year-old female with a full-thickness tear of the superior rotator cuff. (a) MRI shows discontinuity of the superior rotator cuff and fluid retention in the subacromial bursa (arrow) on an oblique coronal fat-saturated proton density-weighted image at the initial examination. (b) Oblique sagittal proton density-weighted MR image shows the muscle region and segmented area (dotted lines) at the initial examination. (c. d) Measurements of signal intensity within the regions-of-interest over the supraspinatus and infraspinatus muscles were performed on oblique sagittal images on (c) an in-phase image and on (d) a fat image acquired with the 2-point Dixon sequence. Each signal intensity value was represented as S(ln) and S(Fat), and we calculated the fat fraction in supraspinatus and infraspinatus muscles with the formula S(Fat)/S(ln). Fat fraction was calculated as 0.087 in the supraspinatus muscle and as 0.170 in the infraspinatus muscle. (e) After 25 months of follow-up, MRI shows progression of the superior rotator cuff tear and fluid retention in the subacromial bursa (arrowheads) on an oblique coronal fat-saturated proton-density weighted image. (f) Oblique sagittal proton density-weighted MRI shows progression of atrophy and fatty degeneration of rotator cuff muscles, particularly in the supraspinatus muscle. (g, h) Fat fraction within the rotator cuff muscles increased to 0.31 in the supraspinatus muscle and 0.25 in the infraspinatus muscle. The DFfr was 0.31 / 0.087 = 3.56 in the supraspinatus and 0.25/0.17 = 1.47 in the infraspinatus muscles.



IV. Discussion

There was a noticeable pattern in this research where females had a greater rate of change in the fat fraction compared to men in the group with full-thickness tears. Prior studies have shown that gender is a significant indicator of supraspinatus fatty infiltration {m/24/}, with female patients potentially experiencing quicker progression of fatty degeneration compared to male patients [11]. The current findings further suggest that gender is a contributing factor in the acceleration of fat percentage.

Multiple studies have analyzed the natural progression of fatty infiltration in the rotator cuff muscles. These studies have found that moderate fatty infiltration (Goutallier stage 2) typically develops in the supraspinatus muscle around 54.1 months after the onset of non-traumatic shoulder pain, and in the infraspinatus muscle around 56.4 months after the onset of non-traumatic shoulder pain. These investigations have shown a correlation between the quantity of torn tendons and the speed at which fatty infiltration progresses. However, the connection between the extent of the rotator cuff tear and the pace of fatty infiltration has not yet been fully understood. In this study, both the supra- and infraspinatus muscles exhibited a more rapid advancement of fatty degeneration in the group with full-thickness tears compared to what has been previously documented. Conversely, the group without full-thickness tears demonstrated a significantly slower progression of fatty degeneration compared to what has been described in previous studies. However, there was no notable disparity in the DFfr across groups having a follow-up MRI interval of less than or more than 2 years. Studies have shown that fatty degeneration worsens within one year after surgery in cases of re-tear following rotator cuff repair. Additionally, it is probable that some patients with full-thickness rotator cuff tears experience significant fatty degeneration of the rotator cuff muscles shortly after the tear occurs. Our study found that the DFfr did not show a significant difference even when the follow-up MRI interval was extended. This suggests that the rate of increase in fat fraction is not consistent. Instead, it appears to increase rapidly in the early stages after a rotator cuff tear and then slow down over time.

We have also shown quantitatively that the fatty degeneration of the rotator cuff muscles advanced considerably over time in the group of patients who had CTA. Reverse shoulder arthroplasty is now the preferred surgical therapy for advanced CTA. However, its limited use, high risk of complications, and invasive nature remain significant challenges {m/14/}. By quantifying the fat fraction and understanding how fatty degeneration of rotator cuff muscles naturally develops over time, we can predict the progression to cuff tear arthropathy (CTA) and choose early treatment for rotator cuff tears to prevent irreversible joint disease.

There were many constraints in our investigation. Initially, we included a limited cohort of patients. Accumulating cases of these individuals is challenging due to the lack of regular long-term follow-up visits when surgery is not feasible. Specifically, a more extensive sample size is required to assess the group with full-thickness tears that demonstrate the advancement of fatty degeneration over time, as well as the group with severe partial-thickness tears. Furthermore, due to the nature of this research being retrospective, the intervals between follow-up MRI scans were not consistent. The current research proposed that the DFfr may not be constant, however, more investigation is required via many observations at shorter time intervals to examine this matter with greater accuracy.



V. Conclusion

We have demonstrated the progression of fatty degeneration in the rotator cuff muscles over time in patients experiencing shoulder pain using quantitative MRI. Our findings indicate that the full-thickness tear group exhibits significantly greater and more quantifiable progression of fatty degeneration in the rotator cuff compared to the group without full-thickness tears. We have also offered quantitative evidence that supports earlier results indicating that cautious observation in cases with full-thickness rips of the rotator cuff is likely to result in gradual fatty degeneration of the rotator cuff. This degeneration reduces the capacity to successfully do primary rotator cuff repair and increases the likelihood of complications such as CTA. Gaining insight into the normal progression of fatty degeneration in the rotator cuff muscles, as shown in this research, is crucial for predicting alterations in shoulder joint function after a rotator cuff rupture and determining the optimal time for therapeutic intervention.

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