# PATTERN RECOGNITION FOR MAGNETIC RESONANCE KNEE IMAGING USING CONVOLUTIONAL NEURAL NETWORK

ZHANG XINYU

FACULTY OF ENGINEERING UNIVERSITY OF MALAYA KUALA LUMPUR

2018

# PATTERN RECOGNITION FOR MAGNETIC RESONANCE KNEE IMAGING USING CONVOLUTIONAL NEURAL NETWORK

ZHANG XINYU

# RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BIOMEDICAL ENGINEERING

FACULTY OF ENGINEERING UNIVERSITY OF MALAYA KUALA LUMPUR

2018

# UNIVERSITY OF MALAYA ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: ZHANG XINYU

Matric No: KQB160003

Name of Degree: Master of Biomedical Engineering

Title of Project Paper/Research Report/Dissertation/Thesis ("this Work"):

Pattern Recognition for Magnetic Resonance Knee Imaging using Convolutional

Neural Network

Field of Study: Biomedical Engineering

I do solemnly and sincerely declare that:

- (1) I am the sole author/writer of this Work;
- (2) This Work is original;
- (3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
- (4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
- (5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya ("UM"), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
- (6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature

Date:

Subscribed and solemnly declared before,

Witness's Signature

Date:

Name:

Designation:

#### ABSTRACT

Nowadays, knee osteoarthritis is a popular disease all over the world. Cartilage degeneration is the performance of osteoarthritis. It is important to research on the characteristic of cartilage. Magnetic resonance imaging provides prominent result in the assessment of osteoarthritis disease. In this project, convolutional neural network was used to identify the region of knee cartilage. 9600 magnetic resonance images were used as dataset where 3440 images were cartilage and 6160 images were background. Each image is 100\*100 pixels. GoogLeNet model was the selected CNN model for training data. Nvidia digits was the platform under the Linux system for training data. After training, trained model was imported in OpenCV doing localization. Another 40 images were used for testing model. Then, manually cropping of cartilage was done in MATLAB. At last, the confusion matrix of accuracy of CNN recognition came out.

#### ABSTRAK

Kini, osteoarthritis lutut adalah penyakit yang popular di seluruh dunia. Kemerosotan terdedah kepada pencapaian osteoarthritis. Adalah penting untuk penyelidikan terhadap ciri rawan. MRI adalah cara yang baik untuk melakukan penilaian penyakit osteoarthritis. Dalam projek ini, CNN digunakan untuk mengenal pasti kawasan rawan lutut. Imej resonans magnetik 9600 digunakan sebagai dataset yang 3440 imej rawan dan 6160 imej adalah latar belakang. Setiap imej adalah 100 \* 100 piksel. Model GoogLeNet adalah model CNN terpilih untuk data latihan. Nvidia digit adalah platform di bawah sistem Linux untuk data latihan. Selepas latihan, model terlatih telah diimport di OpenCV melakukan penyetempatan. 40 imej yaug digunakan untuk model ujian. Kemudian, penanaman rawan secara manual dilakukan di MATLAB. Akhirnya, matriks kekeliruan ketepatan pengiktirafan CNN keluar.

## ACKNOWLEDGEMENTS

I would like to express my special thanks of gratitude to my supervisor (Ir. Dr. Lai Khin Wee) who guided me to do this project on the topic, who also helped me in doing a lot of research and I came to learn a lot of new things I am really thankful to him. Secondly, I would also like to thank my friends Yong Ching Wai who helped me a lot in this project. Lastly, I would like to express my gratitude to my father and mother who always support and encourage me.

v

# TABLE OF CONTENTS

ABSTRACT	iii
ABSTRAK	iv
ACKNOWLEDGEMENTS	v
TABLE OF CONTENTS	vi
LIST OF FIGURES	vii
LIST OF TABLES	viii

CHA	PTER 1: INTRODUCTION	.1
1.1	Introduction	.1
1.2	Problem statement	.3
1.3	Objective	.4
1.4	Project outline	.5

CHA	APTER 2: LITERATURE REVIEW	6
2.1	Osteoarthritis	
2.2	Magnetic resonance imaging (MRI)	
2.3	Machine learning	
	2.3.1 Convolutional neural network (CNN)	
	2.3.2 LeNet, Alexnet and GoogLenet	
2.4	Nvidia Digits	
2.5	OpenCV	
2.6	Cartilage segmentation	

# 

3.1	Image pre-processing	21
3.2	Image training	23
3.3	Image testing	
3.4	Image cropping	

СНА	PTER 4	4: RESULTS AND DISCUSSION	27
4.1	Results		27
	4.1.1	Training model	27
	4.1.2	Image localization	31
	4.1.3	Image cropping	37
4.2	Discuss	ion	40

CHAPTER 5: CONCLUSION	.41
REFERENCES	.42

# LIST OF FIGURES

Figure 2.1: Healthy joint and osteoarthritis. Source from https://www.ster	n-cell-
therapy.com.au/arthritis/	7
Figure 2.2: A is the T1-weighted image and B is T2-weighted image (Tavares Jú	nior et
al., 2012)	9
Figure 2.3: Architecture of CNN(Peng, Wang, Chen, & Liu, 2016)	13
Figure 2.4: Architecture of LeNeT-5(LeCun et al., 1998)	15
Figure 2.5: Architecture of AlexNet (Krizhevsky et al., 2012)	15
Figure 2.6:Architecture of GPU (Singla, Mudgerikar, Papapanagiotou, & Yavuz,	2015)
	17
Figure 2.7: An example of segmentation of cartilage. Source from http://qure.ai/wh	at-we-
do.html#musculoskeletal1	20
Figure 3.1: Workflow of image pre-processing	21
Figure 3.2: Image classification	22
Figure 3.3: Parameter setting	23
Figure 3.4: Workflow of coding	25
Figure 4.1: Real-time performance of CNN training	27
Figure 4.2: Learning rate of CNN training	28
Figure 4.3: The predictions of test image	28
Figure 4.4: The first convolution and pooling layer of GoogLeNet	29
Figure 4.5: The last classifier and softmax	30
Figure 4.6: Localization procedure	31
Figure 4.7: The testing image and localization image of number 1-8	32
Figure 4.8: The testing image and localization image of number 9-16	33
Figure 4.9: The testing image and localization image of number 17-24	34
Figure 4.10: The testing image and localization image of number 25-32	35
Figure 4.11: The testing image and localization image of number 33-40	36
Figure 4.12: Cropping image of cartilage	37
Figure 4.13: Ground Truth Bounding Box of Otsu Optimal Threshold2 image	37
Figure 4.14: Confusion matrix images	38

# LIST OF TABLES

Table 4.1: Confusion matrix of the testing results	28
Ŭ	
Table 4.2: The result of confusion matrix	

#### **CHAPTER 1: INTRODUCTION**

#### **1.1** Introduction

Knee osteoarthritis is the most common chronic degenerative bone and joint disease in the elderly (Arden & Nevitt, 2006). There are about 350 million people who were suffering from osteoarthritis in the world. Osteoarthritis seriously hampers the work of patients, becoming the second most common cause of losing labor who is over 50 years old, second only to heart disease (Abate et al., 2008). The incidence of osteoarthritis is increased significantly with the increasing age. Besides the age, osteoarthritis is associated with inheritance, sex, age, obesity, trauma, and inflammation (Blagojevic, Jinks, Jeffery, & Jordan, 2010).

The assessment of osteoarthritis disease mainly relies on medical imaging, such as Xray, MRI, arthrography, arthroscopy, ultrasound. MRI has the high resolution of soft tissue, can be any surface imaging and multi-parameter, multi-sequence imaging (Y. J. Lee, Sadigh, Mankad, Kapse, & Rajeswaran, 2016). MRI can display cartilage directly multi-faceted imaging overcomes the CT scan spine can only scan the surface of the defects, it can check multiple segments one time. The thickness of the different regions of the knee femoral cartilage can reflect the health of the knee joint and the degree of arthritis (Blumenkrantz & Majumdar, 2007; Seungbum Koo & Andriacchi, 2007; S Koo, Gold, & Andriacchi, 2005), and the changes of morphological curvature of cartilage are closely related to the pathological condition of osteoarthritis (Bowers et al., 2008; Folkesson et al., 2008). MRI is noninvasive, reproducible and the most promising in the early imaging of osteoarthritis (Palmer et al., 2013). With the emergence and improvement of new sequences, rapid progress of hardware, MRI in the diagnosis of osteoarthritis also has great potential. Image recognition refers to the artificial intelligence technology, especially the machine learning method, so that the computer can identify the contents of the image. Image classification is a major area of pattern recognition research. Convolution neural network has a wide range of applications in image recognition, especially in the medical field. For medical imaging, the use of convolution neural network can greatly improve the recognition rate, while reducing the requirements of the quality of the original picture, and can reduce the requirements of the number of training samples (Shen, Wu, & Suk, 2017). In this project, we use CNN to identify the region of cartilage and localize the cartilage in knee MRI.

# **1.2 Problem statement**

Osteoarthritis is a public health issue nowadays. There were some methods to detect the osteoarthritis in cartilage. Radiography is the simplest way to detect osteoarthritis, but the articular structure is not clearly visible. Ultrasound also enables imaging at low cost, but due to the physical properties of sound, it cannot assess the deep structure of articular and bone. CT is another approach to detect the osteoarthritis, but CT scan is costly, and invasive. Besides imaging, automatic diagnosis is important in detecting osteoarthritis. There was an efficient method which analyzing the knee cartilage images by X-ray. This method automatically detect the osteoarthritis by using image classification (Shamir, Ling, Scott Jr, et al., 2009). But this method is expensive and is not always preferred. Also, radiography detection through a computer-aided analysis also can quantify the knee osteoarthritis (Shamir, Ling, Scott, et al., 2009), but in this method, the accuracy of classification is not ideal. To simplify machine learning tasks, manually designed or handcrafted features often work. Nevertheless, they have some disadvantages, such as timeconsuming (H. Lee, 2010).

MRI is noninvasive and reproducible, and it has the high resolution of soft tissue. It can control the contrast difference between different tissue. Compared to traditional technologies, convolutional neural network has some advantages, for example, it is a highly efficiency and accuracy recognition method. Also, CNN can deal with complex information. So, in this project, we use convolutional neural network to identify the region of cartilage in knee MRI images.

# 1.3 Objective

The objectives of this project are as followings are:

- 1. To investigate the characteristic and features of knee MRI images.
- 2. To design and develop a convolutional neural network to identify the region of knee cartilage.
- 3. To validate the accuracy of developed CNN using confusion matrix.

uninger in the second

# **1.4 Project outline**

There are five chapters in this report.

Chapter 1 contains the introduction and objective of this project.

Chapter 2 describes the literature review of this project which consists of the background of osteoarthritis and MRI, the class of machine learning and how machine learning related to healthcare, what are Nvidia Digits, the history of CNN, the architecture of LeNet, AlexNet and GoogLeNet, and some algorithms of cartilage segmentation.

Chapter3 describes the method to do the classification of images, how to do image training in Caffe, image testing and analyzing and image cropping.

Chapter 4 describes the results of the trained GoogLeNet model in OpenCV and the manual cropping, also describes the discussion according to the results and the difficulties while doing the project.

Chapter 5 describes the conclusion of this project.

#### **CHAPTER 2: LITERATURE REVIEW**

#### 2.1 Osteoarthritis

Osteoarthritis(OA) is the most common arthropathy in the world, and it can lead to the occurrence of disability. Until 2003, osteoarthritis is the sixth factor causing disability in the world, and it has been predicted to be the fourth leading by 2020 (Woolf & Pfleger, 2003). In the United States, a study showed that about 37% of older people were diagnosed with knee osteoarthritis(Lawrence et al., 2008). The incidence of osteoarthritis is only lower than ischemic heart disease. Osteoarthritis brings pain to the patient, a serious decline in the quality of life, and even loss of ability to work. Due to a series of changes, such as an injury, ageing, inflammation, genetic and some other factors, osteoarthritis can make a difference. Cartilage degeneration is the performance of osteoarthritis. It will be thinning or disappear, leading to reduce the ability to absorb collision joints. In addition, osteoarthritis is also manifested in subchondral bone sclerosis, osteophyte formation, synovial inflammation and so on(Pap & Korb-Pap, 2015). The most significant clinical manifestation of osteoarthritis is joint pain and tenderness. Joint swelling is also the clinical manifestation of osteoarthritis. In the early state limited swelling are around the joints, with the progression of the disease, there will be diffuse joint swelling, bursa thickening or joint effusion symptoms, in the late, palpable osteophytes can be formed in the joints. Due to cartilage destruction and rough joint surface, joint friction sounds mostly occur in the knee (Hochberg, 1997).



Figure 2.1: Healthy joint and osteoarthritis. Source from https://www.stem-celltherapy.com.au/arthritis/

The diagnosing of osteoarthritis disease mainly includes X-ray, MRI, CT, ultrasound etc. X-ray is inexpensive, but only according to changes in joint space to indirectly determine the damage of cartilage. Bone sclerosis, articular cystic degeneration and osteophyte formation are characteristic, but all of them are late changes, so X-ray is lack of value in early diagnosis. MRI has high resolution of soft tissue and can directly show cartilage. MRI is noninvasive and reproducible, and is the most promising in early osteoarthritis imaging. CT joint angiography is an injection of air or non-ionic contrast agent into the joint capsule and then scan. Air or non-ionic contrast agents in good contrast with cartilage formation, whereas hyaline subchondral bone is in good contrast with the cartilage edge, and thus CT can show cartilage damage and thickness. However, due to traumatic puncture, clinical application of CT joint angiography is limited. Ultrasound can reflect the earliest pathological changes of knee osteoarthritis, and can reflect the cartilage focal thinning and defects. The sonogram showed a partial thinning and disappearance of the cartilage hypoechoic band, and the echo of the subchondral bone was enhanced in these lesion areas, which may suggest elephantiac sclerosis and cartilage defects in the subchondral bone.

# 2.2 Magnetic resonance imaging (MRI)

The principle of Magnetic resonance imaging (MRI) is the RF pulse by applying a certain specific frequency to the human body in the static magnetic field. The hydrogen protons in the body are excited and occur magnetic resonance phenomenon. After the pulse stop, the proton generates a MR signal during relaxation. Through the MR signal reception, spatial coding and image reconstruction and other processing, the MRI is generated. MRI used to quantitatively analyzing damages in cartilage (Gamio, Lee, & Majumdar, 2004). MR imaging techniques can be used to assess cartilage morphology and biochemical composition, volume quantification. The advantage of MRI imaging is that it allows controlling the contrast differences to show different tissue types(Gold, Chen, Koo, Hargreaves, & Bangerter, 2009; Link, Stahl, & Woertler, 2007). Image spatial resolution, image signal-to-noise ratio (SNR) and image acquisition protocol are the important factors affecting MRI evaluation (Recht, Goodwin, Winalski, & White, 2005). The type of contrast used in cartilage imaging is critical to the SNR of the cartilage itself(Gold et al., 2009). The imaging protocol of the knee normally includes T1-weighted spin echoes sequence, T2-weighted gradient echo sequence, proton density weighted image and T2 plus 9-fat compressive sequence(Roemer et al., 2005). T1-weighted highlights the tissue longitudinal relaxation difference, T2-weighted highlights the tissue longitudinal relaxation difference. TI is used to observe the anatomical structure, T2 is used to show tissue lesions. Currently, the 3D-FS-SPGR sequence is commonly used in imaging of cartilage, which combines three-dimensional imaging and fat suppression (FS) techniques to show high articular cartilage and low-signal surrounding tissue clearly (Disler, 1997; Recht, Piraino, Paletta, Schils, & Belhobek, 1996).



Figure 2.2: A is the T1-weighted image and B is T2-weighted image (Tavares Júnior et al., 2012)

# 2.3 Machine learning

In 1949, Donald Hebb proposed a theory called Hebbian learning principle, which explained the changes in the brain neurons in the learning process(Hebb, 1949). This is the first step in the field of machine learning. In 1952, Arthur Samuel designed a checker program that can be learned(Samuel, 1967). It can build a new model by observing the move of the pieces and use it to improve their playing chess skills. He proposed the concept of machine learning and defined it as a field of study that made the computer possess a certain ability through unclear programming. In 1957, Rosenblatt proposed the second model, the Perceptron which is closer to the machine learning model nowadays(Rosenblatt, 1958). In 1960, Widrow proposed a differential learning rule for the practical training of Perceptron (Widrow & Hoff, 1960). In 1969, Minsky and Papert exposed the essential defects of the Perceptron (Minsky & Papert, 1969). In 1970, Linnainmaa proposed the reverse pattern automatic calculus algorithm (Linnainmaa, 1970). In 1981, Werbos proposed the multi-layer perceptron (MLP) by BP algorithm under neural network(Werbos, 1982). In 1986, J. R. Quinlan proposed the famous ML algorithm - decision tree, which is the ID3 algorithm (Quinlan, 1986). In 1995, Vapnik and Cortes proposed support vector machine (SVM) which is a breakthrough in machine learning (Cortes & Vapnik, 1995). In 1997 Freund and Schapire proposed another effective machine learning model - AdaBoost which is described as an enhanced combination of weak classifiers (Freund, Schapire, & Abe, 1999). In 2001, Breiman proposed a combined model of another multi-decision tree - Random Forest (RF) which can avoid the overfitting (Breiman, 2001).

Machine learning is a subfield of computer science. In the field of artificial intelligence, machine learning has gradually developed into the study of pattern recognition and computational science theory. In the field of data statistics, machine learning is a way to design complex models and algorithms to achieve predictive

functionality. Machine learning is focusing on the prediction, learning from training data, and predicting based on known characteristics. Data mining focuses on discovering unknown properties from the data (Mitchell, 1999). In the field of business, machine learning is known for its predictive analysis.

Decision tree learning is a common machine learning method. Decision tree learning uses a decision tree as a predictive model that maps the observed results of an object and gives a deduction for its target value. The neural network is another machine learning method. It is an algorithm that inspired by the biological neural network (LIANG et al.). The computational structure of the neural network is composed of a coupled artificial neuron group, which communicates information and computes by coupling formula. Deep learning is another branch of machine learning. It enables many machine learning applications to be achieved, and expand the whole field of artificial intelligence. Deep learning is composed of multiple hidden layers in artificial neural networks, it attempts to simulate the process of the human brain. Support vector machine (SVM) is a method of supervised learning, mainly used in the pattern recognition, statistical classification and regression problems (D. Qin, Yang, Wang, & Zhang, 2011). The SVM training algorithm can classify the new case into one of the two categories and make itself a nonprobabilistic binary linear classifier.

Healthcare is one of the fastest growing industries in the world nowadays. Drug mining, medical imaging, and medical diagnosis are three main areas applications of machine learning in healthcare. Disease diagnosis is one of the many labor-intensive jobs in the medical system, it is an area which machine learning algorithms good at. Most of the diagnostic data are based on imaging, such as X-rays, magnetic resonance and ultrasound images, as well as genomic profiles, epidemiological data, blood tests, and biopsy results. Thus, this provides a lot of data for training neural networks and machine

learning. Currently, most of the medical images are interpreted by the doctor. However, due to the subjectivity and the difference between the different readers, human interpretation of the image is often one-sided. Machine learning plays a key role in improving the accuracy of the diagnosis. It helps identify the target part to support the expert.

university

#### 2.3.1 Convolutional neural network (CNN)

Convolutional neural network (CNN) is a kind of machine learning model which under deep supervision. It is a highly efficient identification method. In the 1960s, Hubel and Wiesel found the network structure could reduce the complexity of feedback neural network efficiently while researching the neurons of local sensitivity and direction selection in the cortical, they proposed the concept of the receptive field (Hubel & Wiesel, 1962). In the 1980s, Fukushima proposed the concept of neocognitron (Fukushima & Miyake, 1982). Neocognitron can be considered as the first implementation network of convolution neural network. In 1998, CNN was put forward by Yann LeCun (LeCun, Bottou, Bengio, & Haffner, 1998). CNN is essentially a multi-layer perceptron. It uses the method of local connection and weight sharing. In 2012, Krizhevsky who proposed Alex Net won the championship in the large-scale image database ImageNet image classification contest, making convolution neural network to be the focus of the academic community (Krizhevsky, Sutskever, & Hinton, 2012).



Figure 2.3: Architecture of CNN(Peng, Wang, Chen, & Liu, 2016)

Classical CNN consists of a convolution layer (C), a descending sample layer (S) and a fully connected layer (F) (Bottou, Bengio, & Le Cun, 1997). The essence of convolution layer is the feature extractor, with the deep network model, can extract the input signal of the deep information automatically. The descending layer is pooling layer which sampling the feature graph and preserving the useful information while reducing the amount of data. The full connected layer (such as the SoftMax layer) is usually located at the end of the network, the previous layers transformation and feature extraction are classified and processed. The basic structure of CNN consists of two special neuronal layers, one is the feature extraction layer, and the other is the feature mapping layer. In feature extraction layer, the input of each neuron is connected to the local acceptance field of the previous layer and extracts the local feature. After the local feature is extracted, its positional relationship with other features is determined. In feature mapping layer, each computing layer of the network consists of multiple feature maps, each feature map is a plane and the weights of all neurons on the plane are equal. The feature map has a displacement invariance. Each convolution layer in a convolutional neural network follows a computational layer for local averaging and secondary extraction.

### 2.3.2 LeNet, Alexnet and GoogLenet

LeNet-5(LeCun et al., 1998) model uses the alternately connected convolution layer and the down sampling layer to carry forward the forward the input image, and then output probability distribution through full connection layer.



Figure 2.4: Architecture of LeNeT-5(LeCun et al., 1998)

AlexNet (Krizhevsky et al., 2012) has five layers of convoluted networks, about 650,000 neurons and 60 million training parameters, the network size greatly exceeds the LeNet-5. The large image classification database ImageNet (Y. Qin, Lu, Xu, & Wang, 2015) is the training data set of AlexNet. ImageNet provides 1000 categories of 1.2 million images for training, the number and type of images are significantly greater the previous data sets.



Figure 2.5: Architecture of AlexNet (Krizhevsky et al., 2012)

GoogLeNet (Szegedy et al., 2015)is composed of a convolutional neural network. GoogLeNet neural network is based on the LeNet neural network model deepening the depth and width of the network model. It deepens the depth of the LeNet model, a number of layers with parameters reached to 22 and independent layers more than 100. The pixel size of GoogLeNet network is 224x224. GoogLeNet network uses RGB three colors channel. At the same time, to avoid gradient disappearance, two losses are added at different depths to ensure the gradient return. In order to prevent over-fitting, reduce the error and strengthen the characteristics of the model, after all the convolution operation, linear correction unit (Re-LU) is used, and finally SoftMax as a classifier. The increased width of GoogLeNet network is reflected by the Inception module added in the structure. The number of training parameters of GoogLeNet built with the Inception module is only 1/12 of the AlexNet, but the image classification accuracy on ImageNet of GoogLeNet is about 10% higher than the AlexNet.

#### 2.4 Nvidia Digits

Nvidia digits is a web application tool for graphical and visualize Caffe. Digits is Deep Learning GPU (graphics processing unit) Training System.



Figure 2.6: Architecture of GPU (Singla, Mudgerikar, Papapanagiotou, & Yavuz, 2015) Currently there are three main frameworks for using GPU support for deep learning: Theano, Torch and Caffe. The core language of Caffe (Convolutional Architecture for Fast Feature Embedding) is C ++, and it supports command line, Python and MATLAB interface. Nvidia digits is running on CUDA (compute unified device architecture )and Caffe(Jia et al., 2014). CUDA (Compute Unified Device Architecture) is a generic parallel computing architecture introduced by NVIDIA that enables the GPU to solve complex computational problems (De Donno, Esposito, Tarricone, & Catarinucci, 2010). CUDA can run only on the equipment which has a NVIDIA graphics card. The purpose of Nvidia digits is to integrate the existing Deep Learning development tools to simplify the task of designing, training and visualizing DNN (deep neural networks).

## 2.5 OpenCV

OpenCV (Bradski & Kaehler, 2008) is Open Source Computer Vision Library. It consists of a series of C functions and some C + + function. OpenCV implements many common algorithms for image processing and computer vision, such as feature detection and tracking, motion analysis, target segmentation and recognition, and 3D reconstruction. OpenCV has a modular structure. Core functionality is a compact module that defines the basic data structure, including the dense multidimensional Mat array and the basic functions used by its modules. Image processing module, which includes linear and non-linear image filtering, geometric transformation (reset size, radiation and perspective deformation, general basic table reset mapping), color space conversion, histogram, etc. Video analysis module, which includes action judgment, background weakening and target tracking algorithm. Calib3d based on multi-view geometry, which includes planar and stereo camera calibration, object posture judgment, stereo matching algorithm, and 3D element reconstruction. The object is an instantiation module of the target and predefined categories (e.g. face, eyes, cars). HighGUI, a user function interface, used to read and output data, create a window. ML is a machine learning library that contains some statistical-based classification and clustering tools.

#### 2.6 Cartilage segmentation

The cartilage segmentation and quantitative analysis of knee MRI images are the necessary basis for disease diagnosis. In the MRI of the knee joint, the articular cartilage is small and narrow, in different MRI sections, the cartilage morphology is quite different, and the contrast between the cartilage tissue and the surrounding muscle, meniscus, ligament and other tissue contrast difference is small. With the increase symptoms of knee osteoarthritis, the thickness and the contrast of the cartilage changes in the MRI. The articular cartilage segmentation algorithm is based on deformation model mainly includes active shape model, an active contour model, an active appearance model, statistical shape model and so on. Gonzalez et al. proposed a MRI image fusion algorithm based on time series to improve the performance of the active shape model (González & Escalante-Ramírez, 2013). Vincent et al. proposed a fully automated knee articular cartilage segmentation algorithm based on the active appearance model that obtains statistical shapes and image information from training data and applies it to new images (Vincent, Wolstenholme, Scott, & Bowes, 2010). Except the segmentation based on the deformation, there are also some algorithms based on the map. Park et al. proposed a strategy which from rough to subdivide to get the relevant bone map and segmentation(S. Lee, Park, Shim, Yun, & Lee, 2011; Park, Lee, Yun, & Lee, 2012). Wang et al. proposed a method of segmentation without registration, which is obtained by using the threedimensional histogram of the gradient direction as the image similarity measurement (Wang, Donoghue, & Rueckert, 2013). Knee cartilage segmentation can also be segmented or classified as clustering, combining traditional image segmentation methods with intelligent algorithms to make segmentation results more accurate. Folkesson et al. used two-step k-nearest neighbor methods to classify voxels and separate cartilage pixels from non-cartilage pixels (Folkesson, Dam, Olsen, Pettersen, & Christiansen, 2007).

Zhang et al. automated segmentation of knee cartilage from multi-contrast MRI using a spatial dependency SVM classifier(Zhang, Lu, & Marziliano, 2013).



Figure 2.7: An example of segmentation of cartilage. Source from http://qure.ai/what-we-do.html#musculoskeletal1

### **CHAPTER 3: METHODOLOGY**

## **3.1** Image pre-processing

48 patients' data were used in this project for training the convolution neural network. Another 20 patients were chosen for testing the trained CNN model. The format of data is DICOM (Digital Imaging and Communication in Medicine). RadiAnt DICOM Viewer software is used to convert DICOM to JPEG (Joint Photographic Experts Group) format. Each patient has 160 frames. The best two images were chosen which can clearly see the cartilage from each patient. Using MATLAB each image is cropped into 100 small images with the size of 100\*100 pixels. According to the feature of cartilage, manually divide these images into two categories which are "cartilage" and "background". This resulted in 3440 cartilage images and 6160 background images.



Figure 3.1: Workflow of image pre-processing



Figure 3.2: Image classification

# **3.2** Image training

For ubuntu setup, first, do the partition for the hard disk under Windows 10, leaving enough zone for installing the ubuntu. Then download ubuntu files from official ubuntu website in an empty U disk. Record the iso file to the U disk. Restart the computer, choose U disk starts, enter ubuntu installation interface. Then follow the instructions to install the ubuntu. For Caffe and Nvidia digits setup, first, download the CUDA installer from the official website. Then install CUDA in ubuntu. Second, install needed libraries and compile the Caffe. Then install and configure DIGITS. Third open the browser, enters "http:// localhost / "in the address bar. Then test an example MNIST.

The computer of this project has the processor of Intel Core i5-7300 and Nvidia GTX1050. The property of graphics card determines the efficiency of CNN training. GoogLeNet model is the selected in this project. For the dataset, image size setting is 256\*256 pixels with grayscale. The learning rate is 0.01, and the epoch is 30. 50% (4800) images are used as training data, 25%(2400) images are used as validation data, and 25%(2400) images are used as testing data. Input the model name and then create the model.

Job Directory /var/lib/digits/jobs/20171011-150140-d634 Disk Size 1.19 GB Network (train/val) train\_val.prototxt Network (deploy) deploy.prototxt Network (original) original.prototxt Solver solver\_prototxt Raw caffe output caffe\_output.log

Dataset	
googlenet2	
Done Wed Oct 11, 03:01:20 PM	
Image Size 255x256 Image Type GRAYSCALE DB backend Imdb Create DB (train) 4800 images Create DB (val) 2400 images Create DB (test) 2400 images	

Figure 3.3: Parameter setting

# **3.3** Image testing

OpenCV with Microsoft Visual Studio can do the visualization of Caffemodel and the localization the cartilage from the knee MRI images. First, download the GoogLeNet files: "snapshot\_iter\_1470.caffemodel" and "deploy.prototxt". Also, the mean jpg image, testing image and the names of classes: "labels.txt". Put these files in the program folder. Try to import Caffe GoogLeNet model. Create and initialize the network through the importer. Check the network read successfully or not. Create a window which size is 100\*100 to scan the testing image. Read and convert an image into the blob. Then input the blob to the network and do the forward communication. Next, get the output of probability. At last, nine images which five in grayscale and four in colormap will output. There are two level thresholds in this programming.

PPM (pixelated probability map) method was implemented in this project. The PPM equals the CPM (cumulative probability map) divided by CM (counter map).

$$Prob_{(j,i)} = CumProb_{(j,i)} \odot \frac{1}{Count_{(j,i)}}$$

Equation 3.1: j is the row, i is the column

The thresholding method is one of the simplest and most widely used in image segmentation techniques(Sahoo, Soltani, & Wong, 1988). Otsu thresholding (Otsu, 1979) is an algorithm used in this project to isolate the highest probability cartilage from the whole image. According to the gray features of the image, Otsu thresholding divides the image into two parts, the background and the target. Then get the target image within cartilage.



Figure 3.4: Workflow of coding

# **3.4** Image cropping

There are 20 patient data for testing, choose 2 images from each patient. After loading the Caffe model in OpenCV, the 40 testing images also do the cropping in MATLAB. Loading the testing image in MATLAB, then running the coding, manually cropped the proper cartilage in the window, then four images will be shown.

Convert Otsu Optimal Threshold 2 image into Ground Truth Bounding Box. This part is also done in MATLAB. Then the cropping image from MATLAB and the Bounding Box image will do a confusion matrix in MATLAB. The confusion matrix is a two-row and two-column table consisting of false positives, false negatives, true positives and true negatives.

## **CHAPTER 4: RESULTS AND DISCUSSION**

# 4.1 Results

### 4.1.1 Training model

The training time for the CNN model is 28 min. The accuracy of the final is 95.667%. Almost from epoch 10 the accuracy can reach 95%. The learning rate of epoch 1 to 10 is 0.01, epoch 10 to 20 is 0.001, and after epoch 20 is 0.0001. The loss and accuracy of training and validation are shown in Figure 4.1. The learning rate of 30 epochs is shown in Figure 4.2.



Figure 4.1: Real-time performance of CNN training



Figure 4.2: Learning rate of CNN training

For testing many images, there are 25% of the dataset for testing, 1540 background images and 860 cartilage images. Table 4.1 shows the confusion matrix of the testing results. In this project, the accuracy of background is 93.7% and the accuracy of cartilage is 96.4%.

Table 4.1: Confusion matrix of the testing results

	Background	Cartilage	Per-class accuracy
Background	1443	97	93.7%
Cartilage	31	829	96.4%

For testing one image, choose one image from dataset, the predictions and the procures that how CNN model predict the test image can be shown. The following figures are the example.





redictions	
cartilage	(100.0%)
background	0.0%

Figure 4.3: The predictions of test image



Figure 4.4: The first convolution and pooling layer of GoogLeNet



# 4.1.2 Image localization

Image localization was done by using OpenCV. Figure 4.6 shows the procedure of localization of cartilage. The first image is the original testing image, the second image is count map, the third image is the cumulative probability map, the fourth image is grayscale probability map, the fifth image is color probability map, the sixth image is color masked probability map, the seventh image is Otsu Optimal Threshold1 image in grayscale, the eighth image is Color Masked Otsu Optimal Threshold1 image, the ninth image is Otsu Optimal Threshold2 image in grayscale, and the tenth image is Color Masked Otsu Optimal Threshold2 image.

Figure 4.7 to figure 4.11 shows the localization images of all the testing images.



Figure 4.6: Localization procedure

Number	Original image	Resulted image
1	S	
2		
3	(L)	
4	S	
5		
6		
7		
8		

Figure 4.7: The testing image and localization image of number 1-8

Number	Original image	Resulted image
9		
10		
11	S	
12		
13	Q.	
14	S Q	
15		
16		

Figure 4.8: The testing image and localization image of number 9-16

Number	Original image	Resulted image
17	B	
18		
19	S	
20	S	
21		
22		
23	2	
24		

Figure 4.9: The testing image and localization image of number 17-24

Number	Original image	Resulted image
25	ST.	
26	(C)	
27		
28		
29	Q	Ň
30		1
31	S	
32	L.	

Figure 4.10: The testing image and localization image of number 25-32

Number	Original image	Resulted image
33		U
34		
35	(C)	
36		
37	(	RA
38		
39	1	
40	Con 1	,

Figure 4.11: The testing image and localization image of number 33-40

# 4.1.3 Image cropping

Figure 4.12 is the procedure of cartilage cropping. The first image is the original testing image, the second one is cropped image, the third one is masked inside the region, the fourth one is masked outside region, and the last one is the binary mask of the region.



Figure 4.12: Cropping image of cartilage

Figure 4.13 is the procedure of convert Otsu Optimal Threshold2 image into Ground Truth Bounding Box. This procedure was done in OpenCV.



Figure 4.13: Ground Truth Bounding Box of Otsu Optimal Threshold2 image

In figure 4.14, the left one is cropping mask image, the right one is the Bounding Box of second threshold image. Then calculate the confusion matrix.



Figure 4.14: Confusion matrix images

Table 4.2 shows the confusion matrix of all the testing images. There are some parameters which can evaluate performance: accuracy, precision, DSC, JI and MCC. The equations are as followings:

Accuracy=(TP+TN)/(TP+TN+FP+FN);

Precision=TP/(TP+FP);

DSC = (2\*TP)/(2\*TP + FP + FN);

JI = TP/(FN+FP+TP);

MCC = ((TP\*TN)-(FP\*FN))/(sqrt((TP+FP) \*(TP+FN) \*(TN+FP) \*(TN+FN)));

DSC is dice similarity coefficient, it is used for comparing the similarity of two samples. If the DSC is closer to 1, that means the two images are more similar. JI is Jaccard index, it is also used to comparing the similarity and diversity between the samples. The more higher value of JI means the higher similarity of samples. MCC is Matthew's correlation coefficient, it is used to measure how well the classification model is performing. It has a range of -1 to 1 where 1 means the completely correct binary classifier and -1 means totally wrong classification.

The average value of accuracy is 0.66965, the precision is 0.33581, DSC is 0.49386, MCC is 0.44685, JI is 0.33816. And the standard deviation of accuracy is 0.11708, precision is 0.09704, DSC is 0.09932, MCC is 0.10523, JI is 0.09622.

No	ТР	FP	TN	FN	TOTAL	DSC	MCC	JI	Accuracy	Precision
1	20900	66616	58752	0	146268	0.3856	0.3345	0.2388	0.544562	0.238813
2	21098	28378	97072	0	146548	0.5979	0.5744	0.4264	0.806357	0.426429
3	37523	54973	53712	0	146208	0.5772	0.4478	0.4057	0.624008	0.405672
4	28200	43216	74952	0	146368	0.5662	0.5005	0.3949	0.704744	0.394869
5	29952	33944	82512	0	146408	0.6383	0.5763	0.4688	0.768155	0.468762
6	23345	28751	93607	805	146508	0.6124	0.5671	0.4413	0.798264	0.448115
7	21716	87220	37192	0	146128	0.3324	0.2441	0.1993	0.403126	0.199346
8	13284	49092	84072	0	146448	0.3511	0.3667	0.213	0.664782	0.212967
9	27306	43350	75732	0	146388	0.5575	0.4958	0.3865	0.703869	0.386464
10	24928	51248	70172	0	146348	0.4931	0.4349	0.3272	0.649821	0.327242
11	30551	58825	56872	0	146248	0.5095	0.5095	0.5095	0.597772	0.341826
12	23016	73680	73680	0	146208	0.3845	0.3093	0.238	0.661359	0.238024
13	24428	64948	56872	0	146248	0.4293	0.3572	0.2733	0.555905	0.273317
14	18144	42832	85472	0	146448	0.4586	0.4452	0.2976	0.707528	0.29756
15	20790	41586	84072	0	146448	0.5	0.4722	0.3333	0.716036	0.333301
16	17710	35486	93312	0	146508	0.4995	0.4911	0.3329	0.757788	0.33292
17	28380	52836	65052	0	146268	0.5179	0.4391	0.3494	0.638773	0.349439
18	21402	83274	41472	0	146148	0.3395	0.2607	0.2045	0.430208	0.204459
19	26164	86632	33312	0	146108	0.3766	0.2538	0.232	0.407069	0.231959
20	23010	58686	64612	0	146308	0.4395	0.3842	0.2817	0.598887	0.281654
21	25823	13013	104103	3689	146628	0.7556	0.6941	0.6072	0.886093	0.664924
22	18054	42062	86352	0	146468	0.4619	0.4494	0.3003	0.712825	0.300319
23	23681	55255	67392	0	146328	0.4615	0.406	0.3	0.622389	0.300003
24	10658	23798	111575	657	146688	0.4657	0.4822	0.3035	0.833286	0.309322
25	29648	27788	88992	0	146428	0.6809	0.6272	0.5162	0.810228	0.516192
26	23009	44487	78912	0	146408	0.5085	0.4669	0.3409	0.696144	0.340894
27	22512	29944	94032	0	146488	0.6006	0.5705	0.4292	0.795587	0.42916
28	18034	67082	61152	0	146268	0.3497	0.3179	0.2119	0.541376	0.211876
29	24521	21295	100752	0	146568	0.6972	0.6647	0.5352	0.854709	0.535206
30	15855	37281	93392	0	146528	0.4596	0.4618	0.2984	0.745571	0.298385
31	23716	44380	78191	121	146408	0.5159	0.4684	0.3477	0.696048	0.348273
32	17901	38155	90432	0	146488	0.4841	0.4739	0.3193	0.739535	0.319341
33	24684	38092	83188	484	146448	0.5614	0.5082	0.3902	0.736589	0.393208
34	20034	56142	70172	0	146348	0.4165	0.3822	0.263	0.61638	0.262996
35	26412	66324	53492	0	146228	0.4433	0.3566	0.2848	0.546434	0.284808
36	18532	50624	77232	0	146388	0.4227	0.4023	0.268	0.654179	0.267974
37	33000	53376	59872	0	146248	0.5529	0.4494	0.3821	0.635031	0.382051
38	24453	77963	43752	0	146168	0.3855	0.293	0.2388	0.466621	0.238762
39	21131	44005	81292	0	146428	0.4899	0.4588	0.3244	0.699477	0.324414
40	15972	35364	95192	0	146528	0.4746	0.4763	0.3111	0.758654	0.311127

Table 4.2: The result of confusion matrix

## 4.2 Discussion

In this project, GoogLeNet was used as CNN model. We also tried AlexNet for training data, the accuracy for AlexNet can reach 95.875%, and the time for training is around 7 minutes. Compared these two models, GoogLeNet has more layer than in the neural network, for large amount of data, GoogLeNet can show a better result. For the training time, AlexNet needs less time. However, training these CNN model needs better computer performance, especially graphics processing unit. The better graphics card can save more time in training data.

Except for the model selection, the dataset also can affect the results. The classification of cartilage and background was done by manual, due to the complex structures of cartilage, sometimes there could be some deviation. Also, the amount of dataset also can affect the results. More dataset, the result can be more accurate. However, professional staff such as doctors can help a lot in this part. Their professional skill will do better in segmentation, and this will affect the final accuracy and precision.

In further studies, the recognition of cartilage should be in real-time. There will be a system which can read the data and do the recognition precisely at the same time. In addition, the system should analyze whether the cartilage is normal or in the lesion. Such like this, it will help the doctors in diagnosing.

# **CHAPTER 5: CONCLUSION**

In this paper, we proposed a method using CNN to do the recognition for knee MRI. GoogLeNet was the CNN model which successfully locate the cartilage from knee MRI. Nvidia Digits was the deep neural network platform for training model. OpenCV visualized the localization of the CNN model. And we did the cropping manually in MATLAB, then got the confusion matrix of cropping results and localization results. Furthermore, the suggestion for improvement is getting larger dataset for more accurate results.

#### REFERENCES

- Abate, M., Pelotti, P., De Amicis, D., Di Iorio, A., Galletti, S., & Salini, V. (2008).
  Viscosupplementation with hyaluronic acid in hip osteoarthritis (a review). Upsala journal of medical sciences, 113(3), 261-278.
- Arden, N., & Nevitt, M. C. (2006). Osteoarthritis: epidemiology. *Best practice & research Clinical rheumatology*, 20(1), 3-25.
- Blagojevic, M., Jinks, C., Jeffery, A., & Jordan, K. (2010). Risk factors for onset of osteoarthritis of the knee in older adults: a systematic review and meta-analysis. *Osteoarthritis and cartilage*, *18*(1), 24-33.
- Blumenkrantz, G., & Majumdar, S. (2007). Quantitative magnetic resonance imaging of articular cartilage in osteoarthritis. *Eur Cell Mater*, *13*(7).
- Bottou, L., Bengio, Y., & Le Cun, Y. (1997). *Global training of document processing systems using graph transformer networks.* Paper presented at the Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on.
- Bowers, M. E., Tung, G. A., Trinh, N., Leventhal, E., Crisco, J. J., Kimia, B., & Fleming, B. C.
  (2008). Effects of ACL interference screws on articular cartilage volume and thickness measurements with 1.5 T and 3 T MRI. Osteoarthritis and Cartilage, 16(5), 572-578.
- Bradski, G., & Kaehler, A. (2008). *Learning OpenCV: Computer vision with the OpenCV library*: " O'Reilly Media, Inc.".
- Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20(3), 273-297.
- De Donno, D., Esposito, A., Tarricone, L., & Catarinucci, L. (2010). Introduction to GPU computing and CUDA programming: A case study on FDTD [EM programmer's notebook]. *IEEE Antennas and Propagation Magazine*, *52*(3), 116-122.
- Disler, D. (1997). Fat-suppressed three-dimensional spoiled gradient-recalled MR imaging: assessment of articular and physeal hyaline cartilage. *AJR. American journal of roentgenology*, *169*(4), 1117-1123.
- Folkesson, J., Dam, E. B., Olsen, O. F., Karsdal, M. A., Pettersen, P. C., & Christiansen, C. (2008). Automatic quantification of local and global articular cartilage surface curvature: biomarkers for osteoarthritis? *Magnetic resonance in medicine*, 59(6), 1340-1346.
- Folkesson, J., Dam, E. B., Olsen, O. F., Pettersen, P. C., & Christiansen, C. (2007). Segmenting articular cartilage automatically using a voxel classification approach. *IEEE transactions* on medical imaging, 26(1), 106-115.
- Freund, Y., Schapire, R., & Abe, N. (1999). A short introduction to boosting. *Journal-Japanese* Society For Artificial Intelligence, 14(771-780), 1612.
- Fukushima, K., & Miyake, S. (1982). Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition *Competition and cooperation in neural nets* (pp. 267-285): Springer.
- Gamio, J., Lee, K., & Majumdar, S. (2004). *MRI cartilage of the knee: Segmentation, Analiysis and Visualisation.* Paper presented at the Proc. ISMRM.
- Gold, G. E., Chen, C. A., Koo, S., Hargreaves, B. A., & Bangerter, N. K. (2009). Recent advances in MRI of articular cartilage. *American Journal of Roentgenology*, *193*(3), 628-638.
- González, G., & Escalante-Ramírez, B. (2013). *Knee cartilage segmentation using active shape models and contrast enhancement from magnetic resonance images.* Paper presented at the IX International Seminar on Medical Information Processing and Analysis.
- Hebb, D. (1949). The organization of behaviour, Ed: John Wiley y Sons.

Hochberg, M. (1997). Osteoarthritis–clinical features and treatment. *Primer on the rheumatic diseases. 11th edn. Atlanta: Arthritis Foundation*, 218-221.

Hubel, D. H., & Wiesel, T. N. (1962). Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *The Journal of physiology*, *160*(1), 106-154.

- Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., . . . Darrell, T. (2014). *Caffe: Convolutional architecture for fast feature embedding.* Paper presented at the Proceedings of the 22nd ACM international conference on Multimedia.
- Koo, S., & Andriacchi, T. P. (2007). A comparison of the influence of global functional loads vs. local contact anatomy on articular cartilage thickness at the knee. *Journal of biomechanics*, 40(13), 2961-2966.
- Koo, S., Gold, G., & Andriacchi, T. (2005). Considerations in measuring cartilage thickness using MRI: factors influencing reproducibility and accuracy. *Osteoarthritis and Cartilage*, 13(9), 782-789.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *Imagenet classification with deep convolutional neural networks.* Paper presented at the Advances in neural information processing systems.
- Lawrence, R. C., Felson, D. T., Helmick, C. G., Arnold, L. M., Choi, H., Deyo, R. A., . . . Hunder, G. G. (2008). Estimates of the prevalence of arthritis and other rheumatic conditions in the United States: Part II. Arthritis & Rheumatology, 58(1), 26-35.
- LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE, 86*(11), 2278-2324.
- Lee, H. (2010). Unsupervised feature learning via sparse hierarchical representations: Stanford University.
- Lee, S., Park, S. H., Shim, H., Yun, I. D., & Lee, S. U. (2011). Optimization of local shape and appearance probabilities for segmentation of knee cartilage in 3-D MR images. *Computer Vision and Image Understanding*, *115*(12), 1710-1720.
- Lee, Y. J., Sadigh, S., Mankad, K., Kapse, N., & Rajeswaran, G. (2016). The imaging of osteomyelitis. *Quantitative imaging in medicine and surgery*, 6(2), 184.
- LIANG, Y.-T., Kun, L., Zheng-Yun, Y., Ya-Jun, M., Wei-Dong, L., Jian-Ming, B., . . . Zi-Yan, D. Track reconstruction in the BESIII muon counter.
- Link, T. M., Stahl, R., & Woertler, K. (2007). Cartilage imaging: motivation, techniques, current and future significance. *European radiology*, *17*(5), 1135-1146.
- Linnainmaa, S. (1970). The representation of the cumulative rounding error of an algorithm as a Taylor expansion of the local rounding errors. *Master's Thesis (in Finnish), Univ. Helsinki*, 6-7.
- Minsky, M., & Papert, S. (1969). Perceptrons.
- Mitchell, T. M. (1999). Machine learning and data mining. *Communications of the ACM, 42*(11), 30-36.
- Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE transactions on systems, man, and cybernetics, 9*(1), 62-66.
- Palmer, A., Brown, C., McNally, E., Price, A., Tracey, I., Jezzard, P., . . . Glyn-Jones, S. (2013). Non-invasive imaging of cartilage in early osteoarthritis. *Bone Joint J*, *95*(6), 738-746.
- Pap, T., & Korb-Pap, A. (2015). Cartilage damage in osteoarthritis and rheumatoid arthritis [mdash] two unequal siblings. *Nature Reviews Rheumatology, 11*(10), 606-615.
- Park, S. H., Lee, S., Yun, I. D., & Lee, S. U. (2012). Automatic bone segmentation in knee MR images using a coarse-to-fine strategy. Paper presented at the Medical Imaging: Image Processing.
- Peng, M., Wang, C., Chen, T., & Liu, G. (2016). NIRFaceNet: A Convolutional Neural Network for Near-Infrared Face Identification. *Information*, 7(4), 61.
- Qin, D., Yang, J., Wang, J., & Zhang, B. (2011). *IP traffic classification based on machine learning*. Paper presented at the Communication Technology (ICCT), 2011 IEEE 13th International Conference on.
- Qin, Y., Lu, H., Xu, Y., & Wang, H. (2015). *Saliency detection via cellular automata*. Paper presented at the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.
- Quinlan, J. R. (1986). Induction of decision trees. Machine learning, 1(1), 81-106.

- Recht, M. P., Goodwin, D. W., Winalski, C. S., & White, L. M. (2005). MRI of articular cartilage: revisiting current status and future directions. *American Journal of Roentgenology*, 185(4), 899-914.
- Recht, M. P., Piraino, D. W., Paletta, G. A., Schils, J. P., & Belhobek, G. H. (1996). Accuracy of fat-suppressed three-dimensional spoiled gradient-echo FLASH MR imaging in the detection of patellofemoral articular cartilage abnormalities. *Radiology*, *198*(1), 209-212.
- Roemer, F. W., Guermazi, A., Lynch, J. A., Peterfy, C. G., Nevitt, M. C., Webb, N., . . . Felson, D. T. (2005). Short tau inversion recovery and proton density-weighted fat suppressed sequences for the evaluation of osteoarthritis of the knee with a 1.0 T dedicated extremity MRI: development of a time-efficient sequence protocol. *European radiology*, *15*(5), 978-987.
- Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological review, 65*(6), 386.
- Sahoo, P. K., Soltani, S., & Wong, A. K. (1988). A survey of thresholding techniques. *Computer* vision, graphics, and image processing, 41(2), 233-260.
- Samuel, A. L. (1967). Some studies in machine learning using the game of checkers. II—recent progress. *IBM Journal of research and development*, *11*(6), 601-617.
- Shamir, L., Ling, S. M., Scott Jr, W. W., Bos, A., Orlov, N., Macura, T. J., . . . Goldberg, I. G. (2009). Knee X-ray image analysis method for automated detection of Osteoarthritis. *IEEE Transactions on Biomedical Engineering*, 56(2), 407-415.
- Shamir, L., Ling, S. M., Scott, W., Hochberg, M., Ferrucci, L., & Goldberg, I. G. (2009). Early detection of radiographic knee osteoarthritis using computer-aided analysis. *Osteoarthritis and Cartilage*, *17*(10), 1307-1312.
- Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. *Annual Review of Biomedical Engineering*(0).
- Singla, A., Mudgerikar, A., Papapanagiotou, I., & Yavuz, A. A. (2015). *Haa: Hardwareaccelerated authentication for internet of things in mission critical vehicular networks.* Paper presented at the Military Communications Conference, MILCOM 2015-2015 IEEE.
- Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., . . . Rabinovich, A. (2015). *Going deeper with convolutions.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.
- Tavares Júnior, W. C., Faria, F. M. d., Figueiredo, R., Matushita, J. P. K., Silva, L. C., & Kakehasi,
  A. M. (2012). Bone attrition: a cause of knee pain in osteoarthritis. *Radiologia* Brasileira, 45(5), 273-278.
- Vincent, G., Wolstenholme, C., Scott, I., & Bowes, M. (2010). Fully automatic segmentation of the knee joint using active appearance models. *Medical Image Analysis for the Clinic: A Grand Challenge*, 224-230.
- Wang, Z., Donoghue, C., & Rueckert, D. (2013). *Patch-based segmentation without registration: application to knee MRI.* Paper presented at the International Workshop on Machine Learning in Medical Imaging.
- Werbos, P. J. (1982). Applications of advances in nonlinear sensitivity analysis *System modeling and optimization* (pp. 762-770): Springer.
- Widrow, B., & Hoff, M. E. (1960). Adaptive switching circuits. Retrieved from
- Woolf, A. D., & Pfleger, B. (2003). Burden of major musculoskeletal conditions. *Bulletin of the World Health Organization*, *81*(9), 646-656.
- Zhang, K., Lu, W., & Marziliano, P. (2013). Automatic knee cartilage segmentation from multicontrast MR images using support vector machine classification with spatial dependencies. *Magnetic resonance imaging*, *31*(10), 1731-1743.