A Survey focusing on the various medical imaging techniques for the assessment of Osteoarthritis

Tejaswini N P
Professor& Research Scholar
Department of ISE
NMIT, Bengaluru.

Dr. Gururaj Murtugudde
Assistant Professor& Research Supervisor
Department of CSE
REVA University, Bengaluru

Abstract:
In contemporary healthcare, musculoskeletal ailments and articular disorders pose significant challenges, primarily afflicting older populations. Among these conditions, osteoarthritis (OA) commonly targets the human knee joint. While OA can impact various joints such as the spine, fingers, thumbs, hips, knees, and toes, its prevalence is notably high in the knee and hip joints. This discussion focuses specifically on knee joints. Knee osteoarthritis presents a formidable health concern, characterized by severe pain and the potential for lasting disability. Its detection often relies on assessing changes in internal knee tissues, including cartilage, meniscus, and subchondral cartilage. Magnetic Resonance Imaging (MRI) serves as a crucial diagnostic tool, offering detailed images of the knee joint to measure structural alterations. MRI utilizes powerful magnets, radio waves, and sophisticated software to generate comprehensive internal body images.

Osteoarthritis (OA), MR Images, Cartilage, knee segmentation.
DOI Number: 10.48047/NQ.2022.20.13.NQ88510 Neuroquantology 2022; 20(13): 4198-4204

Introduction:
Musculoskeletal disorders (MSDs) have emerged as a significant global health priority, impacting over 1.7 billion individuals globally [1]. The treatment of MSDs can be costly, and misdiagnosis may lead to serious complications. These disorders encompass a range of conditions affecting bones, joints, and muscles. Among the varied types of MSDs are tendinitis, carpal tunnel syndrome, osteoarthritis, rheumatoid arthritis, fibromyalgia, and bone fractures. Musculoskeletal imaging through radiographs encompasses acquisition, analysis, and decision-making processes, applicable to various musculoskeletal structures such as bones, joints, and soft tissues affected by injuries. The automated diagnosis of disorders not only facilitates treatment but also aids in therapy planning and provides guidance for interventions.In recent times, there has been a growing demand for advanced computational methods to aid in the diagnosis of Musculoskeletal Disorders (MSDs). The development of a system capable of automatically discerning between normal and abnormal radiographs streamlines workflow, expediting patient treatment. Moreover, such systems alleviate the burden on radiologists, reducing fatigue and potentially enhancing diagnostic accuracy. While automatic recognition systems offer valuable insights into the prevalence and impact of disorders, they have yet to match the expertise of the best radiologists.[2]Medical images may suffer from noise, potentially compromising result reliability or concealing musculoskeletal conditions. ([3],[4]). Certain studies have

necessitated manual interventions, a process prone to errors, time-consuming, and labour-intensive. ([5], [6])In recent years, Knee Osteoarthritis (OA) has become increasingly prevalent not only among aging individuals but also in the younger population, affecting approximately 30%-40% of younger adults. OA, a degenerative condition, lies at the core of chronic disability. This widespread joint ailment induces pain and dysfunction, particularly among older individuals, often accompanying progressive degeneration of diarthrodial joint tissues.Accurate detection of knee osteoarthritis mandates precise Cartilage Segmentation. However, the process of segmenting cartilage from MR images is time-consuming compared to manual methods and is prone to inaccuracies. An automated segmentation approach becomes imperative for consistently precise detection of osteoarthritis. Below Figure 1a depict the anterior and posterior views of the knee and its respective parts.

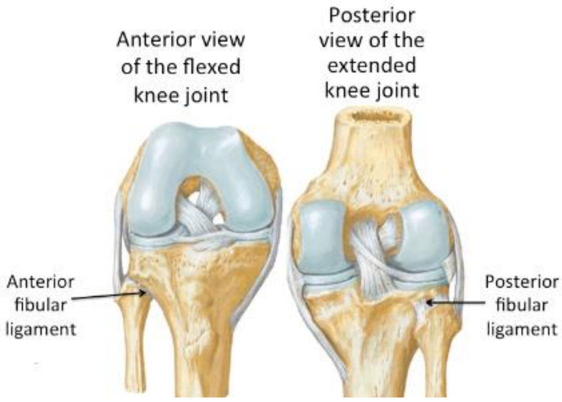

Figure 1. anterior and posterior views of the knee

Literature Survey

In the work by Maxim D. Ryzhkov et al. [7], the challenges associated with knee cartilage segmentation are discussed, offering a critical analysis of methods presented in the literature over the years. Various techniques and methodologies are introduced in the paper to address these challenges.Semi-automatic methods involve user intervention to assist the algorithm in locating the initial points for cartilage segmentation. On the other hand, automatic methods initiate segmentation by identifying adjacent bones. There exist multiple approaches for cartilage extraction, with edge detection methods proving effective, especially in cases where the cartilage and surrounding tissues exhibit plain surfaces.Recent surveys suggest that both semi-automatic and fully automatic segmentation algorithms hold promise in becoming standard techniques for quantifying cartilage surface and volume. These advancements signify significant progress in the field, offering potential solutions to the complexities associated with knee cartilage segmentation.

In their 2018 study, Cem M. Deniz et al. [8], proposed a novel approach for automatic proximal femur segmentation using MR images, integrating Statistical Shape Models and deformable models with Convolutional Neural Networks (CNNs). Traditionally, MRI studies have primarily focused on specific regions of interest (ROI) within the proximal femur, such as the femoral neck and head. However, recent advancements have led to a shift towards investigating the entire proximal femur to better understand its mechanical properties, rather than just isolated sub-regions.The CNN model introduced by Deniz et al. significantly reduces the time required for manual segmentation while also delivering accurate results. By combining Statistical Shape Models and deformable models with CNNs, their approach offers a robust and efficient method for automating proximal femur segmentation from MR images. This advancement holds promise for enhancing research into bone mechanics and improving diagnostic capabilities in orthopaedic medicine.

In their 2013 study, Julio Carballido-Gamio et al. [9], introduced a novel technique for analysing knee cartilage in three dimensions (3D) using MR images. Their approach leverages a visualization tool that facilitates the generation of 3D cartilage thickness maps in both one-dimensional (1D) and 3D formats.

In their 2012 study, M.S. Mallikarjunswamy et al. [10], introduced a method aimed at segmenting, visualizing, and quantifying knee articular cartilage to measure cartilage thickness. This technique proves particularly beneficial for the early detection of osteoarthritis in affected patients.The approach employed by Mallikarjunswamy et al. utilizes both semi-automatic and automatic techniques for measuring knee thickness in both two-dimensional (2D) and three-dimensional (3D) contexts. Additionally, they incorporated statistical measures to ensure accuracy, precision, and validation of their results.By combining these methods, the study offers a comprehensive framework for assessing knee articular cartilage, providing valuable insights into disease progression and facilitating early diagnosis in osteoarthritis patients.The primary indication of knee osteoarthritis (OA) often involves the morphological deterioration of articular cartilage. MR imaging offers significant potential for both qualitative visualization and quantitative analysis of knee cartilage.This method represents a valuable advancement in the field, providing clinicians and researchers with a practical tool for assessing cartilage thickness and morphology in 3D, thereby enhancing the understanding and diagnosis of knee OA.

In their 2018 study, Archit Raj et al. [11], introduced an Automated Cartilage Segmentation technique aimed at improving the assessment of advanced Knee Osteoarthritis, considering the intricate 3D structure of knee cartilage. Their approach relies on utilizing the U-Net network architecture, along with methods focusing on data preprocessing, labeling, training, and testing.The U-Net network architecture serves as the backbone of their methodology, providing a robust framework for effectively segmenting knee cartilage in 3D images. Key components of their approach include meticulous data preparation, accurate labeling, and rigorous training and testing procedures.By implementing these methods, Raj et al. contribute to enhancing the performance of automated cartilage segmentation, which holds significant potential for advancing the diagnosis and management of Knee Osteoarthritis.

Han Sang Lee et al. (2018) [12], introduced a novel method for segmenting knee cartilage from MRI images, leveraging Deep Segmentation Networks (DSNs). Their approach reframes the cartilage segmentation task by focusing on segmenting the Bone Cartilage Complexes (BCC) and bones first.By adopting a 2.5D segmentation strategy, their method generates three-plane results, which are then integrated using a majority voting scheme to enhance segmentation accuracy. This innovative technique aims to improve the precision and reliability of knee cartilage segmentation from MRI images, offering potential advancements in diagnostic accuracy and treatment planning for knee-related conditions.

Francois Lauze et al. (2013) [13], introduced a Convolutional Neural Network (CNN) employing deep learning architecture, which has demonstrated successful applications in segmenting 2D images. Their study extends CNN methodology to voxel classification in 3D images, a novel approach for segmentation tasks.In particular, they utilize a Triplanar Convolutional Neural Network for cartilage segmentation, capitalizing on its ability to analyze multiple perspectives simultaneously. By leveraging CNNs and their triplanar architecture, Lauze et al. aim to enhance the precision and efficiency of cartilage segmentation from 3D image datasets. This methodological advancement holds promise for improving diagnostic accuracy and treatment planning in medical imaging.

In their 2017 study, Fang Liu et al. [14], employed Deep Convolutional Neural Network (CNN) and three-dimensional (3D) simplex deformable modeling to enhance the accuracy and efficiency of cartilage and bone segmentation within the knee joint. Their approach involved developing a fully automated segmentation pipeline by combining a semantic segmentation CNN with 3D simplex deformable modeling. The CNN model, specifically SegNet, served as the cornerstone of the segmentation process, enabling high-confidence pixel-wise multi-class tissue classification. The 3D simplex deformable modeling further refined the SegNet output, preserving overall shape and maintaining smooth surfaces for musculoskeletal structures. The fully automated segmentation technique underwent testing using publicly available knee image datasets, where it outperformed existing state-of-the-art segmentation methods. Additionally, the method demonstrated versatile segmentation performance across morphological and quantitative musculoskeletal MR images with varying tissue contrasts and spatial resolutions.Overall, the proposed fully automated segmentation technique showcased superior segmentation performance compared to non-automated and semi-automated methods, offering significant advancements in knee joint image analysis and diagnostic accuracy.

In their study, Berk Norman et al. [15], employed a 2D U-Net Convolutional Neural Network for the fully automated segmentation of cartilage and meniscus from knee MRI scans. Their objective was to assess the shape, structure, and relaxometry in comparison to other manual and semi-automated state-of-the-art methods. The investigation utilized 638 MR imaging volumes obtained at 3T from two data sets: SPGR T1ρ-weighted and 3D double echo steady state (3D-DESS) images. For automatic segmentation, they implemented a deep learning model based on the U-Net Convolutional Neural Network architecture, which automatically segments the cartilage and meniscus segments. The performance of the automatic segmentation was evaluated against manual segmentation performed by experts and radiologists. The assessment involved comparing the results of automatic segmentation with manual segmentation using the Dice Coefficient overlap metric. This approach represents a significant advancement in knee MRI analysis, offering a reliable and efficient method for segmenting cartilage and meniscus regions. The comparison with manual segmentation provides insights into the accuracy and effectiveness of the automated segmentation process.

Felicia Aldrin [16], introduces the concept of "Mechanized Segmentation of the Meniscus" in knee MR images. The aim is to perform 3D segmentation of tissues within the knee joint to identify injuries and abnormalities, facilitating computer-aided diagnosis and treatment planning for patients with knee issues. Manual segmentation, however, is time-consuming and prone to inter-rater variability, highlighting the need for automated segmentation methods. With recent advancements in machine learning, automated segmentation and classification tasks have significantly improved, making them a natural choice for the challenging task of menisci segmentation. Aldrin proposes and compares two fully automated machine learning segmentation methods: Random Forest based on Haar-like features, and the deep learning technique 2D U-Net Fully Convolutional Network (FCN). Both methods undergo testing and comparison for the segmentation of 18 menisci from 3D Magnetic Resonance (MR) images. This research underscores the potential of machine learning algorithms in automating the segmentation process, thereby enhancing the accuracy and efficiency of knee MR image analysis for diagnosis and treatment planning purposes.

Alexander Tack et al. [17] introduced an innovative approach for the automatic segmentation of menisci from MR images. Their model integrates Convolutional Neural Network (CNN) with Statistical Shape Models to enhance accuracy and efficiency. The method's accuracy was evaluated using 88 MR image samples that underwent manual segmentation. The evaluation included measurements of meniscal volume and tibial coverage across different age groups afflicted with Osteoarthritis. The proposed method achieved an accuracy of 88.3%, demonstrating its effectiveness in accurately segmenting menisci from MR images. This method represents a significant advancement in automated segmentation techniques, offering potential benefits for diagnosis, treatment planning, and research in Osteoarthritis and related knee pathologies.

In their 2014 study, Meenaz H. Shaikh et al. [18], introduced novel techniques utilizing Active Shape Models (ASM) for knee joint segmentation. ASM relies on statistical analysis of structural variations in 3D objects, starting with an average model shape and iteratively refining the structure based on image data. Another method introduced is the Active Appearance Model (AAM), which incorporates both shape and gray level data, assuming a linear relationship between object shape and surrounding intensity patterns. However, AAM's reliance on such assumptions may not be suitable for knee joint segmentation due to its inherent limitations.Deformable Models, on the other hand, offer robustness, address boundary gaps, and allow for the integration of boundary elements, making them more suitable for knee joint segmentation. However, knee joint image segmentation remains a highly complex task.Segmentation methods for knee joints generally fall into three categories: manual, semi-automatic, and fully automatic. Manual segmentation, while accurate, is time-consuming and requires user intervention. Semi-automatic methods aim to automate some processing steps to alleviate user burden. Fully automatic methods involve advanced and complex processing steps with fewer limitations. These advancements aim to enhance the efficiency and accuracy of knee joint segmentation, crucial for effective diagnosis and treatment planning.

In their 2016 work, Jianxu Chen et al. [19], proposed an innovative Deep Learning (DL) framework for 3D image segmentation. Their approach combines a Fully Convolutional Network (FCN) and a Recurrent Neural Network (RNN) to handle intra-slice and inter-slice perspectives separately. This dual-network architecture allows for comprehensive analysis of three-dimensional biomedical images.The authors evaluated their method on two distinct 3D biomedical image segmentation tasks and demonstrated its capability to achieve state-of-the-art results. Their framework introduces a novel model that leverages the high performance of 2D deep structural designs to enhance the segmentation accuracy and efficiency in 3D contexts.By integrating FCN and RNN components, the proposed framework offers a promising solution for advanced 3D image segmentation, contributing to improved biomedical image analysis and diagnostic capabilities.

In their 2013 study, K. Mori et al. [20], introduced a novel method called Tri-planar Convolutional Neural Network (CNN) for knee cartilage segmentation using MR images. The segmentation of skeletal structures in medical images relies heavily on accurate voxel or pixel categorization.The Tri-planar 2D CNNs proposed by Mori et al. excel at categorizing voxels from 3D images with exceptional accuracy. By employing this method, MRI slices undergo segmentation, resulting in outcomes that surpass those achieved by radiologists. The Tri-planar CNN approach demonstrates effectiveness in terms of Dice Similarity Coefficient (DSC), responsiveness, meticulousness, and accuracy.This innovative method represents a significant advancement in knee cartilage segmentation, offering improved diagnostic capabilities and potentially enhancing the accuracy of medical image analysis in orthopaedic settings.

In their 2010 study, P. Dodin et al. [21] introduced an algorithm designed to automatically segment human knee cartilage from 3D MRI scans without requiring human intervention. This approach enabled continuous monitoring of osteoarthritis progression in the knee joint. The algorithm operates by resampling the MRI data and employing texture analysis to identify the external surface of the cartilage, considering variations in bone surfaces. One notable advancement of this technique is its ability to quantify not only the overall cartilage volume but also to delineate the upper part of the femur and the lower part of the tibia separately. Unlike previous methods, which lacked the capability to segment knee cartilage into distinct surfaces, this new approach addresses complex cartilage structures commonly found in individuals with osteoarthritis[22]. The development of this automatic segmentation technique addressed several key challenges identified in previous methods, resulting in a more accurate assessment of cartilage volume with minimal error. This advancement holds promise for improving the diagnosis and management of osteoarthritis by providing clinicians with detailed and reliable information about knee joint health.

Conclusion

The reviewed studies and methodologies aim to address critical gaps in detecting various abnormalities within knee joints. These approaches strive to enhance the accuracy, efficiency, and comprehensiveness of detecting abnormalities such as cartilage degradation, meniscal injuries, and other structural irregularities. Through advanced techniques like Convolutional Neural Networks (CNNs), Statistical Shape Models, and machine learning algorithms, researchers endeavour to automate segmentation processes, reduce manual intervention, and improve diagnostic precision. By leveraging 3D MR images, these methods enable the identification of subtle abnormalities and provide valuable insights into knee health and pathology. Moreover, these methodologies are crucial for addressing inter-rater variability, reducing processing time, and enhancing the overall diagnostic workflow. Ultimately, the goal is to develop robust and reliable tools that can aid clinicians in diagnosing knee conditions promptly and accurately, thereby improving patient outcomes and treatment strategies.

Future Enhancement

Develop automatic expert systems that gain all the knowledge of experts and benefit from pattern recognition techniques. We aim to solve as much as possible of the problems unsolved by others and to improve accuracy. We should benefit from the experience gained from other researchers and make use of deep learning techniques as CNN. Different types of robust features will be applied to propose a reliable automatic system for musculoskeletal disorders detection and classification. The proposed techniques is planned for fully automated non-contrast MRI application for detection and segmentation of knee bones.

References

[1] R. E. Marx, Bone and bone graft healing, Oral and maxillofacial surgeryclinics of North America 19 (4) (2007) 455–466.

[2] P. Rajpurkar, J. Irvin, A. Bagul, D. Ding, T. Duan, H. Mehta, B. Yang,K. Zhu, D. Laird, R. L. Ball, et al., Mura dataset: Towards radiologistlevel abnormality detection in musculoskeletal radiographs.

[3] R. Korez, B. Likar, F. Pernuš, T. Vrtovec, Segmentation of pathologicalspines in ct images using a two-way cnn and a collision-based model,in: International Workshop and Challenge on Computational Methodsand Clinical Applications in Musculoskeletal Imaging, Springer, 2017,pp. 95–107.

[4] S. M. R. Al Arif, K. Knapp, G. Slabaugh, Shape-aware deep convolutional neural network for vertebrae segmentation, in: InternationalWorkshop and Challenge on Computational Methods and Clinical Applications in Musculoskeletal Imaging, Springer, 2017, pp. 12–24.

[5] A. Rasoulian, R. Rohling, P. Abolmaesumi, Lumbar spine segmentationusing a statistical multi-vertebrae anatomical shape+ pose model, IEEEtransactions on medical imaging 32 (10) (2013) 1890–1900.

[6] I. Castro-Mateos, J. M. Pozo, M. Pereañez, K. Lekadir, A. Lazary, A. F.Frangi, Statistical interspace models (sims): application to robust 3dspine segmentation, IEEE transactions on medical imaging 34 (8) (2015)1663–1675.

[7] Maxim D .Ryzhkov ”Knee Cartilage SegmentationAlgorithms a critical Literature Review”, BiomedicalImage Science , Supervisors: Dr. K.L. Vincken , Dr. C.Boss.

[8] JianxuChen,Yizhe Zhang, Mark Alber, Danny Z. Chen,Lin Yang ”Combining Fully Convolutional and RecurrentNeural Networks for 3D Biomedical Image segmentation[university of Notre Dame 2016]arXiv:1609.01006v2[cs.CV]6 Sep 2016.

[9] MeenazH.Shaikh , Shraddha Panbude , Anuradha Joshi“Image Segmentation Techniques and its application forknee joints :a Survey“. IOSR Journal of Electronics

andCommunication Engineering (IOSR-JECE),[e-ISSN:2278-2834,p-ISSN:2278-8735.Volume9,Issue5,Ver.IV(SepOct.2014),PP23-28].

[10] Cem M. Deniz,SiyunXiang,SpencerHaliyburton,Arakua Welbeck "Segmentation of the Proximal Femur from MR Images using DeepConvolutional Neural Networks", IEEE Journal ofComputer Vision and Pattern Recognition , 20th March2018.

[11] K.Mori,AdhisPrason,Kersten Petersen, Christian Igel"Deep Feature Learning for Knee Cartilage Segmentationusing a Triplanar Convolutional Neural Network", Journalof Springer-Verlag Berlin Heidelberg,2013.

[12] Julio Carballido-Gamio, Sharmila Majumdar "MRICartilage of the knee: Segmentation, analysis, andvisualizations", IEEE 2013.

[13]M.S.mallikarjun swamy, mallikarjunS. Holi"Knee joint articular cartilage segmentation, visualization and quantification using image processing techniques", journalof international journal of computer applications, March2012(pages36-42).

[14]Quan Wang, DijiaWu,Le Lu, Meizhu Liu, Kim L.Boyer ,and Shaohua Kevin Zhou "Semantic context forestsfor learning–based knee cartilage segmentation in 3d Mr.Images", journal of computer vision and patternrecognition, 22nd April 2014.

[15]carballido-gamio, K.Lee, E.Ozhinsky, S.Majumadar, "MRI cartilage of the knee segmentation, analysis, visualization", journal of proc.intl.soc.mag.reson.med.2004.

[16]Archit Raj , Srikrishnan Vishwanathan , BhavyaAjani ,Karthik Krishnan and Harsh Agarwal "Automatic Knee Cartilage Segmenation Using Fully Volumetric Convolutional Nueral Networks for Evaluation of Osteo Arthritis", journal of IEEE 15th InternationalSymposium on Biomedical Imaging, April 2018.

[17]Hansang Lee, Helen Hong and Junmo Kim "BCDNET:A Novel Method for Cartilage Segmentation of KneeMRI via Deep Segmentation Networks with Bone-Cartilage Complex Modeling", journal of IEEE 15th internationalsymposium on biomedical imaging, April 2018.

[18]Francois Lauze and Mads Nielsen "Deep FeatureLearning for Knee Cartilage Segmentation Using a Triplanar Convolution Neural Network", journal of University of Copenhagen, January 2013.

[19] Fang Liu , Zhaoye Zhou, HyungseokJang, Alexey Samsonov,Gengyan Zhao, and Richard Kijowski, "Deep Convolutional Neural Network and 3DDeformableApproach for Tissue Segmentation inMusculoskeletal Magnetic Resonance Imaging",International Society for Magnetic Resonance in Medicine2017.

[20] Berk Norman, BS, Valentina Pedoia, SharmilaMajumdar, "Use of 2D U-Net Convolutional NeuralNetworks for Automated Cartilage andMeniscusSegmentation of Knee MR Imaging Data toDetermine Relaxometry and Morphometry",MUSCULOSKELETAL IMAGING: Deep Learning forKnee MR Imaging Segmentation 2018.

[21]Felicia Aldrin, "Automated Segmentation of theMeniscus" The 3rd Deep Learning workshop at STH 2017.

[22] Alexander Tack, Anirban Mukhopadhyay, Stefan Zachowa, "Knee Menisci Segmentation using Convolutional Neural Networks: Data from theOsteoarthritis Initiative", Osteoarthritis and Cartilage