"ARTIFICIAL INTELLIGENCE (MACHINE LEARNING) AS A SCREENING TOOL FOR MRI EVALUATION OF NORMAL AND ABNORMAL MEDIAL MENISCUS"

BY

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Dissertation submitted to

B.L.D.E. UNIVERSITY, VIJAYAPURA, KARNATAKA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

DOCTOR OF MEDICINE

IN

RADIO-DIAGNOSIS

UNDER THE GUIDANCE OF

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B.L.D.E (DEEMED TO BE UNIVERSITY), SHRI B M PATIL MEDICAL COLLEGE HOSPITAL & RESEARCH CENTRE, VIJAYAPURA, KARNATAKA

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ACKNOWLEDGEMENT

This piece of work has been accomplished with the grace of almighty God. It brings me great joy to share my heartfelt gratitude to all. This page is devoted to all those who have assisted me in my quest to learn as much as possible.

I want to convey my heartfelt appreciation and sincere thanks to my guide, ***DR.SATISH D PATIL,*** *Head of the Department, Department of Radiodiagnosis, B.L.D.E.U's Shri B. M. Patil Medical College, Vijayapura, for his constant and unfailing support, professional insight, valuable suggestions, motivation and exemplary guidance to carry out and complete this dissertation. I am deeply grateful to him for providing me necessary facilities and excellent supervision to complete this work.*

I want to express my gratitude to ***Dr. R. S. Mudhol MS.*** *(Vice Chancellor),* ***Dr. Aravind Patil MS****. (Principal) and* ***Dr. Rajesh M. Honnutagi MD****. (Medical Superintendent), B.L.D.E.U's Shri B. M. Patil Medical College, Vijayapura, for their support and inspiration.*

My deep thanks to ***Dr. Rajashekhar MuchchandI MD****. (Professor),* ***Dr. Shivanand V. Patil MD****. (Professor)* ***Dr. Satish D. Patil MD.*** *(Professor*

AND HOD), **Dr. Ravi Kumar DNB.** (Associate Professor), **Dr. Siddaroodha Sajjan DNB.** (Associate Professor), **Dr. Vishal S. Nimbal DNB.** (Assistant Professor), **Dr. Suresh Kanamadi MD.** (Senior Resident), **Dr. Nagesh Wadgera MD**. (Assistant Professor), **Dr. Pundalik Lamani MD** (Assistant Professor), **Dr .Pavan Kolekar** (Assistant Professor), **Dr. Divyashree Koppal** (Senior Resident), **Dr. Tejas** (Senior Resident), **Dr. M. M Patil DMRD**, Department of Radio-diagnosis, B.L.D.E.U's Shri B. M. Patil Medical College, Vijayapura, for their valuable suggestions and encouragement which have definitely helped me improve my research work.

I acknowledge my gratitude to my seniors **Dr. Goutham, Dr. Sumana, Dr. Jayanth and Dr. Nihar** my colleagues **Dr. Anudeep, Dr. Siddharth, Dr. Deep, Dr. Sumaiya and Dr. Prama** my juniors **Dr. Sahana, Dr. Prithvi, Dr. Nikhil, Dr. Saketh, Dr. Bharat and Dr. Yashodhan** Postgraduate colleagues, Department of Radiology, B.L.D.E. U's Shri B. M. Patil Medical College, Vijayapura, for their support, advice and help in data collection.

I thank **Ms. Vijaya**, Statistician for her masterly guidance and statistical analysis. I sincerely acknowledge the support and kindness shown towards me by all the staff of Central Library, Shri B. M. Patil Medical College, Vijayapura, at all times.

My heartly thanks to my beloved parents ***Mr. Venugopal Reddy and Mrs. Janaki Devi,*** *My Husband* ***Mr. Venkatramana Reddy*** *and My sister* ***Miss. Varshitha Reddy*** *for their encouragement, support and sacrifices.*

Last but not the least, my sincere thanks to all the patients of this study for their cooperation without which this study would not have been possible.

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ABSTRACT

ARTIFICIAL INTELLIGENCE (MACHINE LEARNING) AS A SCREENING TOOL FOR MRI EVALUATION OF NORMAL AND ABNORMAL MEDIAL MENISCUS

Objective: The most common cause of abnormal meniscus is due to sports-related injuries and the other causes are osteoarthritic and non-osteoarthritic menisci. Sports injuries of meniscus are most common in individuals engaged in high-impact or pivot-heavy activities. The meniscus, a C-shaped piece of cartilage within the knee, cushions and absorbs the applied loads and helps stabilize the knee. A torn/osteoarthritic meniscus can lead to knee pain, swelling, and impairment of function. MRI stands as the most reliable imaging technique to be used in the detection of abnormal meniscus since it offers excellent soft tissue resolution between cartilage, tendons, and ligaments. Although much advancement has been realized in the MRI technology, the diagnosis of meniscal pathologies from MRI images remains one of the difficult areas. The problem is that the signals coming from meniscal tissue are difficult to distinguish from those of the ligaments and other fluid-filled structures surrounding them, therefore making differentiation of normal against injured/degenerated meniscus a very difficult task.

Segmentation of the meniscus, where the meniscus is separated from other structures in the MRI images, forms an important step in improving diagnostic accuracy. Such detailed visualization of the meniscus allows clinicians to evaluate its shape, size, and volume; it can also quantify several specific parameters, such as thickness or degeneration. Manual segmentation

is an extremely tedious and very time-consuming process that requires a lot of expertise and experience. Consequently, manual segmentation is prone to variability when different clinicians apply the technique, causing major inconsistencies in diagnostics. Recent advancements in deep learning and artificial intelligence made possible promising solutions in the automation of segmentation. Algorithm fully and semi-automated were developed and make a wide utilization of machine learning models like CNNs in the identification and segmentation of the meniscus in MRI images. Those models are trained on large, labeled datasets of MRI scans with meniscal tissue and surrounding structures, learning how to distinguish the meniscal tissue from the surrounding structure. The benefits of automated segmentation might involve elevated diagnostic precision, higher workflow efficiency, and lesser human error. while much promise is shown to be held by AI-based methods, the challenges are yet present in reality.

Results: This paper will detail the work to develop a deep learning model based on Mask R-CNN for abnormal meniscus detection and diagnosis from MRI images. The model aims at achieving in detecting normal menisci (healthy) and abnormal menisci (torn/degenerated menisci) with AUC of 0.992 for detecting normal menisci and AUC of 0.962 for detecting abnormal menisci. Overall, this methodology manifests much promise as an effective tool for radiologists to help diagnose injuries of the meniscus.

Conclusion: We introduce a new algorithm that utilizes mask-region convolutional neural networks (CNNs) to effectively identify normal and abnormal meniscus. This advancement lays the groundwork for creating a complete, automated solution for diagnosing this condition.

Keywords:

Meniscus

Magnetic resonance imaging (MRI)

Automatic segmentation

Knee

Mask-Region Convolutional neural networks(RCNN)

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1. INTRODUCTION

The medial meniscus is an essential fibrocartilaginous structure between the knee joint and the femur of the tibia. It performs multiple biological functions indispensable to generating load transmission, shock absorption, and joint stability. Generally, meniscal problems, such as tearing or degeneration, occur to most people, regardless of whether they are athletes or older adults. Meniscal injuries can produce pain and instability of the joint, along with a risk for osteoarthritis if left untreated. Thus, proper management of these injuries can only begin with accurate and early diagnosis.

1.1 Anatomy of meniscus.

One major ligament, many capsular thickenings, and tendinous attachments comprise the knee's medial ligament complex. The superficial medial collateral ligament is commonly called the tibial collateral ligament, whereas the deep medial collateral ligament is also called the mid-third medial capsular ligament. The capsular attachments from the main common tendon of the semimembranosus have been called the posterior oblique ligament.[1]

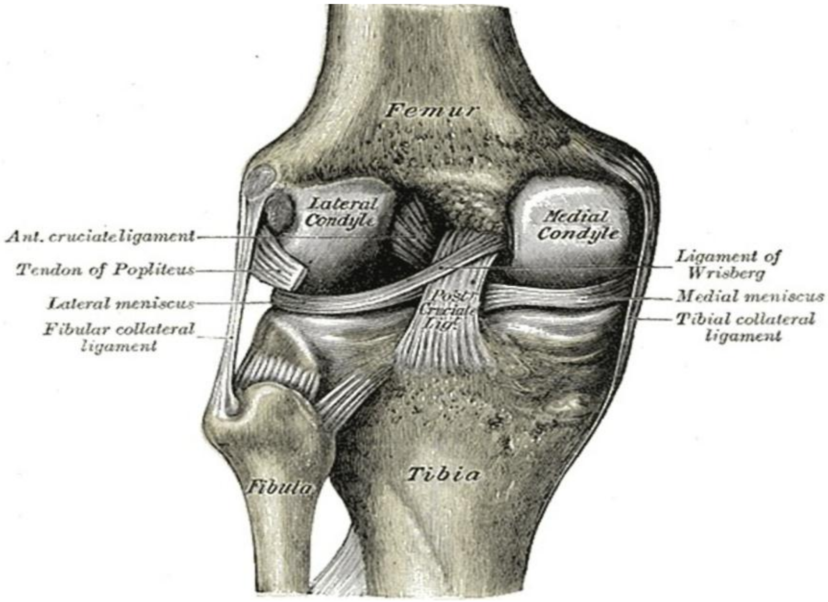


Figure 1

Posterior anatomy of the knee

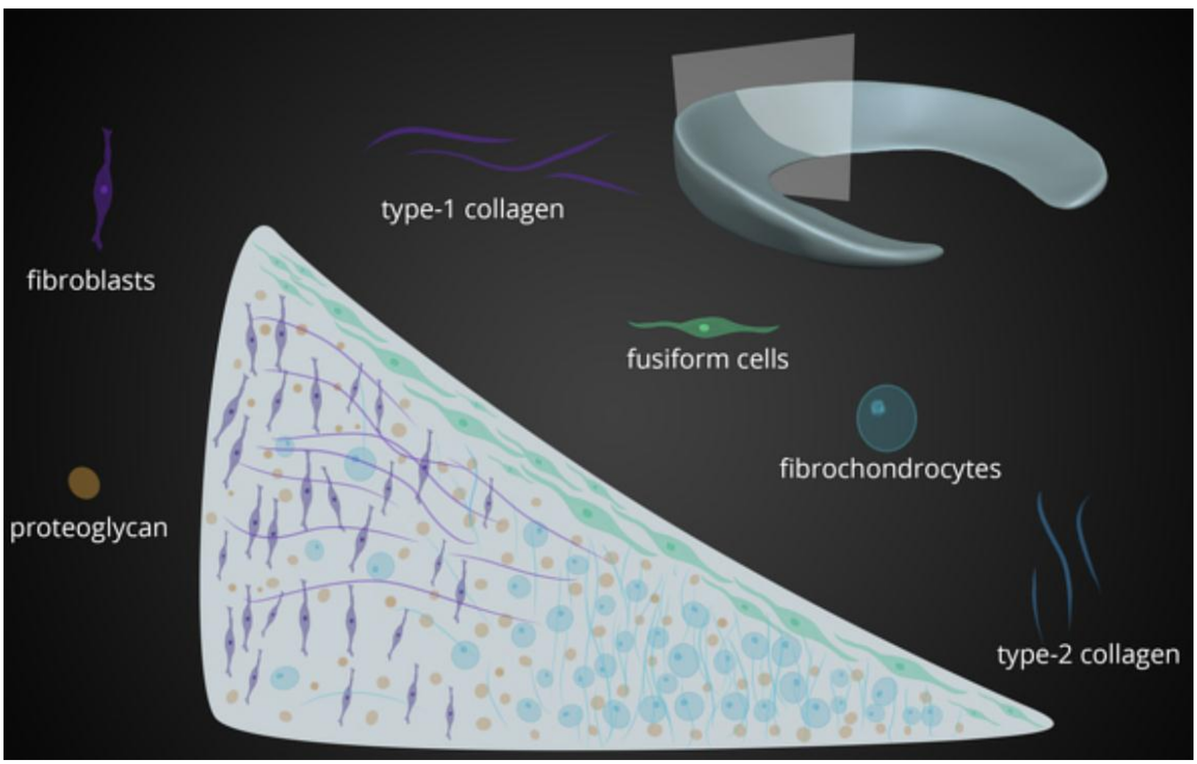


Figure 2

Ultrastructure of the medial meniscus

1.1 MRI in Evaluation of Meniscus

With its excellent soft tissue contrast and non-invasive nature, MRI gives the gold standard assessment for meniscal pathologies. MRI allows complete visualization of the whole meniscus and all the surrounding structures, making it invaluable in detecting tears, degeneration, and other pathologies. Its role in diagnosing meniscal pathologies has been well established in clinical practice and research settings, especially when diagnosis can be challenging by clinical examination alone.

Although these help overcome its disadvantages, MRI image interpretation is highly technical and time-consuming. Hence, meniscal tears, more so at the early stages after an injury, can be challenging to detect and might often go unnoticed due to their subtle manifestations. Also, the number of images produced in a thorough MRI knee exam runs into hundreds, which would take much time and effort even from one of the most experienced radiologists to scrutinize.

A deep learning model can process and interpret these hundreds of MRI pictures. The radiologist’s workflow is greatly facilitated by automation, which also speeds up evaluation and increases diagnostic precision. In particular, picking up abnormalities regarding the medial meniscus makes it an excellent piece of technology in a clinical setting, freeing up time for the radiologist to work on complex cases that require more attention. Second, the model’s ability to analyze images rapidly can decrease workload and even contribute to better patient outcomes by providing quicker, more reliable diagnostic insights.

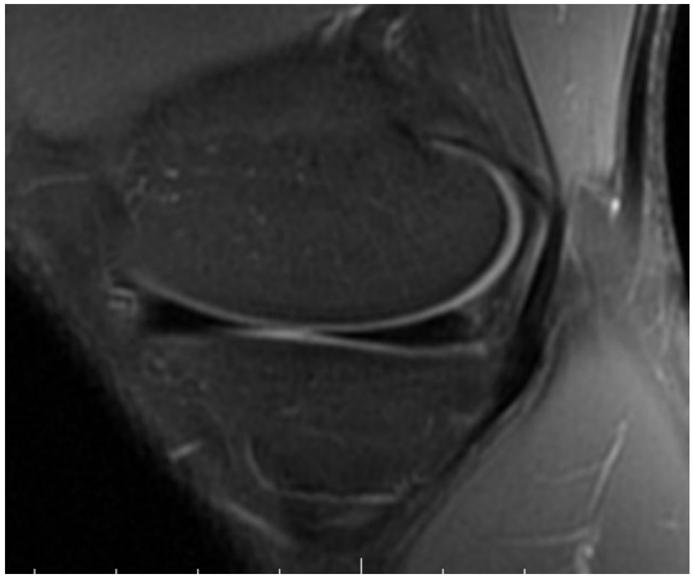


Figure 3

Proton density fat suppressed (Sagittal view) sequence of the knee shows anterior and posterior horn of normal medial meniscus.

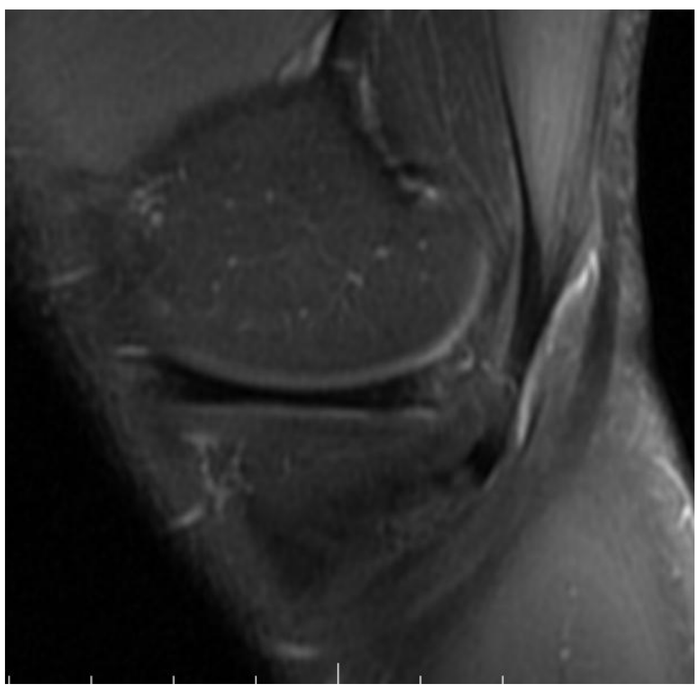


Figure 3

Proton density fat suppressed (Sagittal view) sequence of the knee shows body of normal medial meniscus.

MRI is an ideal non-invasive imaging technique for detecting and assessing meniscal degeneration because it can differentiate between various tissues, including cartilage, ligaments, and fluid within the joint. Abnormal meniscus typically presents with several characteristic features on MRI, reflecting the biochemical and structural changes that occur with the condition.

1. **Signal Intensity Changes**: In a healthy knee, the meniscus appears as a low-signal (dark) triangular structure on T1-weighted and proton-density images, which indicates its dense collagenous composition and lack of free water content. However, when degeneration occurs, the meniscus absorbs more water, increasing its signal intensity, particularly on T2-weighted or fat-saturated images. This results in areas of increased signal intensity, often appearing as bright or hyperintense spots within the typically dark meniscus. These signal changes are often the earliest signs of meniscal degeneration and reflect the breakdown of collagen fibres and increased water content due to cartilage damage.

2. **Meniscal Tears and Morphological Changes**: As degeneration progresses, the structural integrity of the meniscus may be compromised, leading to tears, fissures, or cartilage fraying. On an MRI, these tears appear as linear lines of high signal intensity that reach the surface of the meniscus. The tears may be partial or full-thickness, and in some cases, they may involve complex or horizontal cleavages within the meniscus. These abnormalities often disrupt the typical triangular shape of the meniscus, making it appear irregular or thinned out on MRI slices. Full-thickness injuries, where the meniscus is torn through entirely and meniscal tissue protrudes into the joint space, can worsen joint instability.

3. **Reduction in Meniscal Thickness**: One of the key features of a degenerated meniscus is a reduction in thickness. Over time, as the meniscus deteriorates, the cartilage wears down, becoming thinner and less capable of absorbing shock. This thinning is readily visible on MRI as a decrease in the meniscal body's width or height. A thinner meniscus is more vulnerable to further injury and is less effective at protecting the knee joint from impact. This reduction in thickness is a common finding in advanced meniscal degeneration, especially in older patients or those with osteoarthritis.

4. **Meniscal Extrusion and Displacement**: In severe cases of meniscal degeneration, parts of the meniscus may become displaced or extruded from their normal position within the knee joint. Meniscal extrusion is when the meniscus body is pushed out of the joint space, often due to advanced degeneration or associated ligament damage. This displacement is typically seen in coronal MRI views, where the meniscus can appear outside the boundaries of the tibial plateau. Meniscal extrusion is particularly concerning because it can lead to further joint instability, increased mechanical stress on the articular cartilage, and accelerated joint degeneration, as seen in conditions like osteoarthritis.

1.2 The Role of AI Medical Imaging

AI and, more precisely, ML have become a handy tool in medical imaging in that they can solve almost all problems associated with MRI interpretation when traditional methods are used. AI can be programmed to learn patterns in extensive collections of datasets and is highly competent in image classification, segmentation, and anomaly detection. This is very valid, especially in the case of meniscal injury. Incomplete deviation easily gets overlooked during manual image analysis.

Among them, deep learning, part of machine learning, is an important motivator for the emerging advances in medical imaging. Most of the tasks involved in detecting and classifying meniscal abnormalities are carried out using CNNs predominantly as the architecture for analyzing MRI images. It is possible to automatically learn from large datasets of MRI images with a distinction that denotes the complex structural patterns linked to meniscal tears and degeneration. After training them, these models can be used with great effectiveness to screen a large number of images of MRI within a very short period with the accuracy delivered by a human expert.

There have been promises that AI models will automate various aspects of MRI analysis. Among the most critical ones are normal and abnormal menisci detection and classification. Recently, a deep learning model based on Mask Regional Convolutional Neural Network (Mask R-CNN) has been developed for evaluating meniscal health. The model achieved over 85% diagnostic accuracy when distinguishing between healthy and torn or degenerated menisci through training on images of high patient cohorts. It demonstrated the potential utility of the model as a diagnostic tool, especially in discerning different types of meniscal injuries in different anatomical regions, such as the anterior and posterior horns.

In addition, AI-based models enhance the accurate diagnosis of meniscal tear identification by automatically segmenting the meniscus from other soft tissues in MRI images. This segmentation process is critical to elucidate the anatomical site and extent of the tear. A fast-region convolutional neural network-based AI model was applied to predict tears in the meniscus within a dataset of 1123 knee MRI images. The algorithm yielded an AUC of 0.92 in the identification of meniscal tears and 0.83 in the determination of orientation. This underlines the potential offered by AI towards analyzing complex MRI data streams.

Although this is possible as far as detection and diagnosis are concerned, these AI systems can also predict the course of development for the case of meniscal degeneration. More and more valid and trained AI models will be expected to identify the one more likely to lead to complications: meniscal injury; thus, treatment plans for the patient may be improved based on real-time evaluation.

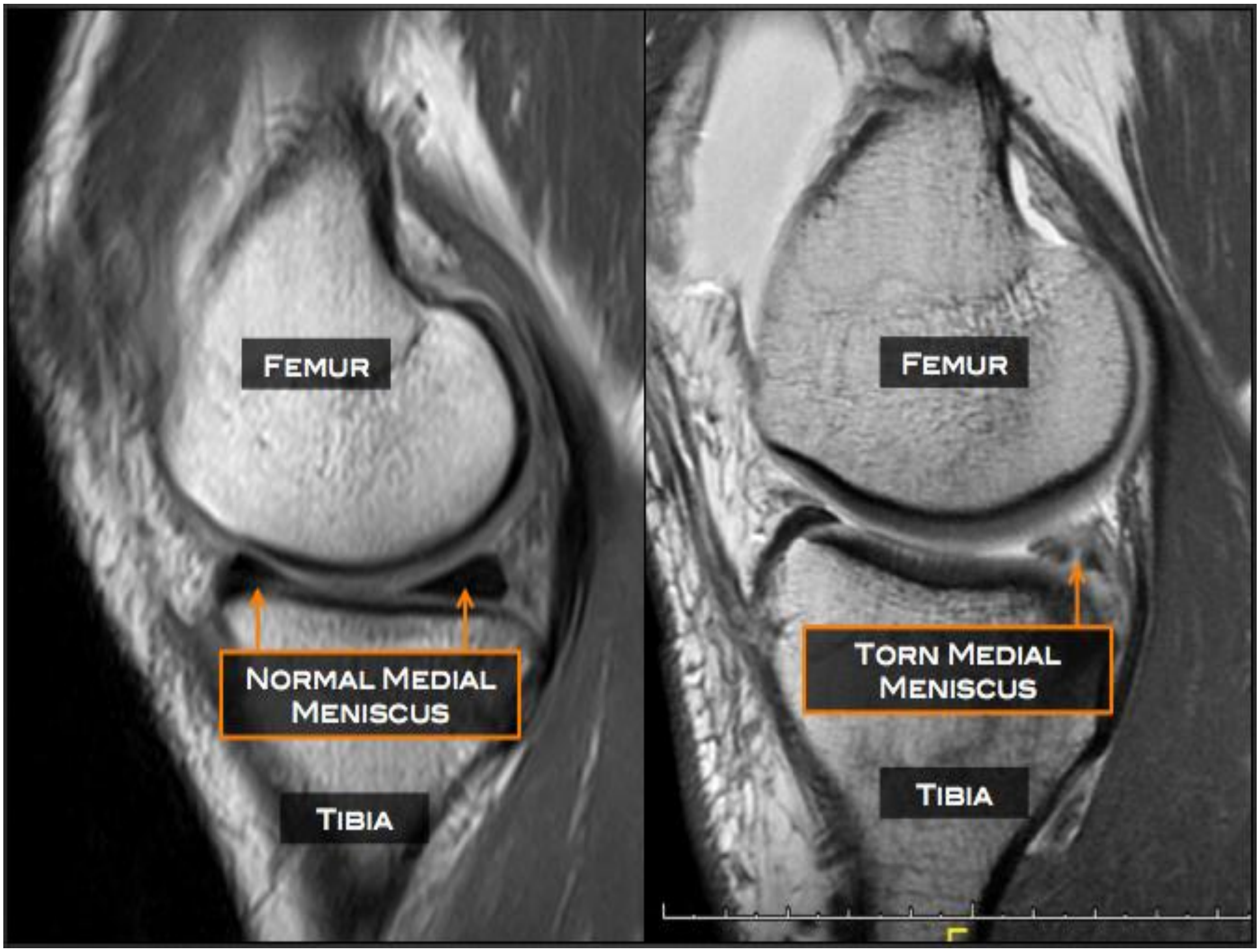


Figure 5

The two MRI examples have a normal medial meniscus (left) and a torn medial meniscus (right), in order to see the sagittal images as an anterior-posterior view. The intact meniscus is viewed as a dark black triangle. The torn meniscus (right) is irregular, with a light line representing the tear traversing it.

1.3 Advantages of AI in Clinical Settings

Several benefits occur in clinical practice with the introduction of AI. First, AI systems are very effective in diagnosing and recording minute abnormalities that human reviewers may have missed, especially for complex cases. Second, it saves time from MRI analysis by preliminary reviewing and flagging suspicious areas for further examination by a radiologist. This reduces the radiologist's workload, reducing the turnaround time for diagnosis. Therefore, intervention and consequent treatment take place earlier.

MRI interpretation also ensures objective and reproducible evaluation in meniscal health by minimizing inter-observer variability. Human mistakes in diagnosis can significantly affect the quality of care since there is a likelihood of errors when carried out by different radiologists. AI provides consistent performance, standardizing the diagnosis process; therefore, treatment has a more uniform conclusion.

Moreover, AI-based screening tools can be integrated with MRI machines, where real-time analysis is also possible while scanning. An even quicker and more effective scanning regimen will be introduced for every patient by future developments in MRI technology, incorporating artificial intelligence. Thus, AI will reduce the time and effort required for manual image evaluation, allowing radiologists to focus entirely on challenging situations.

1.4 Challenges and Future Directions of AI

Although there is a great potential of big advantages of AI in the evaluation of menisci by MRI, challenges remain before such AI systems can enter a clinical workflow, such as a requirement for large diverse datasets to train and validate AI models. MRI scans may depend very much on the used scanner, imaging protocols, and the patient population. Model generalization is guaranteed by the training of the AI model over diverse datasets of various types of images and patient demographics.

Regulatory and ethical contexts are special challenges to AI in healthcare. High validation would be required in a series of clinical trials to demonstrate safety and efficacy. In addition, an AI system needs to have transparency and explainability so that clinicians can trust the decisions and generalizations being made by these models. These systems need to be interpreted and accountable once AI advances further, so that these systems can be successfully applied in practice.

2. AIMS AND OBJECTIVES

To train the model on a large dataset of labeled MRI scans, ensuring accurate differentiation between healthy and pathological menisci.

To develop and evaluate a deep learning-based artificial intelligence model for automated detection and classification of normal and abnormal medial menisci in MRI scans.

3. REVIEW OF LITERATURE

Other relevant works in the literature on this subject can also be included in the papers, discussing deep learning and artificial intelligence for the application of meniscus tears diagnosis based on MRI images.

This model has been named MR Net by Bien et al. in their work of 2018, with a sensitivity result of 76.5% on an internal validation for the detection of the presence of meniscal tears.[2]

Couteaux et al. (2019) trained a mask region-based convolutional neural network (R-CNN) to explicitly localize normal and torn menisci, made it more robust with ensemble aggregation, and cascaded it into a shallow ConvNet to classify the orientation of the tear. They detected and classified meniscus tears using Mask R-CNN; his internal dataset had a correctness of 90.6%.[3]

Roblot et al. (2019) compared the Fast R-CNN and Faster R-CNN models for meniscus tears at maximum accuracy of 90% internal validation. They suggested the development of an AI algorithm to be used in diagnosing and characterizing meniscus tears on MRI of the knee, with a dataset of 1123 MR images for training and 700 for testing. It applied fast-region CNN and faster-region CNN to the three medical diagnosis tasks that are localization of meniscal horns, determination of the existence of a tear, and determination of the orientation of the tear. They divided the task, emulating the procedure of diagnostic work for radiologists and received good metrics of performance: AUC equal to 0.92 for detection of horn for the meniscus, and equal to 0.94 for existence of a tear with an average of 0.83 for orientation, therefore with AUC weighted equal to 0.90 altogether. In a similar study by Bien et al., training set consisted of 1370 MRI scans. There was more crying within the exams in meniscal tissue at 37% rather than 13%. Bien et al. used the convolutional neural network known as MRNet for general abnormalities and specific diagnosis. The AUC for the diagnostic got to 0.847 in diagnosing meniscal tear but marginally lower than that of Roblot's model. However, the research had some drawbacks in it. They included only two T2-weighted MR images per patient in consideration of the data; usually, a knee MRI examination contains about 100 images. Their training was limited only to a normal meniscus and abnormal grade 3 high meniscal signal intensity that was excluded grade 1 and 2 lesions. Overall, the studies point to a strong potential for deep learning algorithms in the near future to assist radiologists in meniscal tear diagnosis but still leave a prospect that significant development is required to produce thorough, end-to-end AI-powered diagnostic tools.[4]

Pedoia et al. attempted to evaluate the ability of deep-learning models to detect and stage severity of meniscus and patellofemoral cartilage lesions in osteoarthritis and anterior cruciate ligament (ACL) subjects. They suggested a 3D convolutional neural network to detect and grade meniscus and cartilage degeneration with 89.8% accuracy to diagnose the meniscus tears.[5]

Fritz et al. Deep CNN achieves a validation accuracy of 91.2% in diagnosing meniscus tears compared to arthroscopic findings.[6]

Conclusion of this chapter, application of MRNet in the year 2021 for detection of meniscus lesions from different machines and also in varying field strengths with an external validation sensitivity of 81%. Collectively, these papers show excellent promise for deep learning to automatically diagnose meniscus tears from MRI input: most of them get more than 85% accuracy in internal validation but most struggle with external validation on diverse datasets.

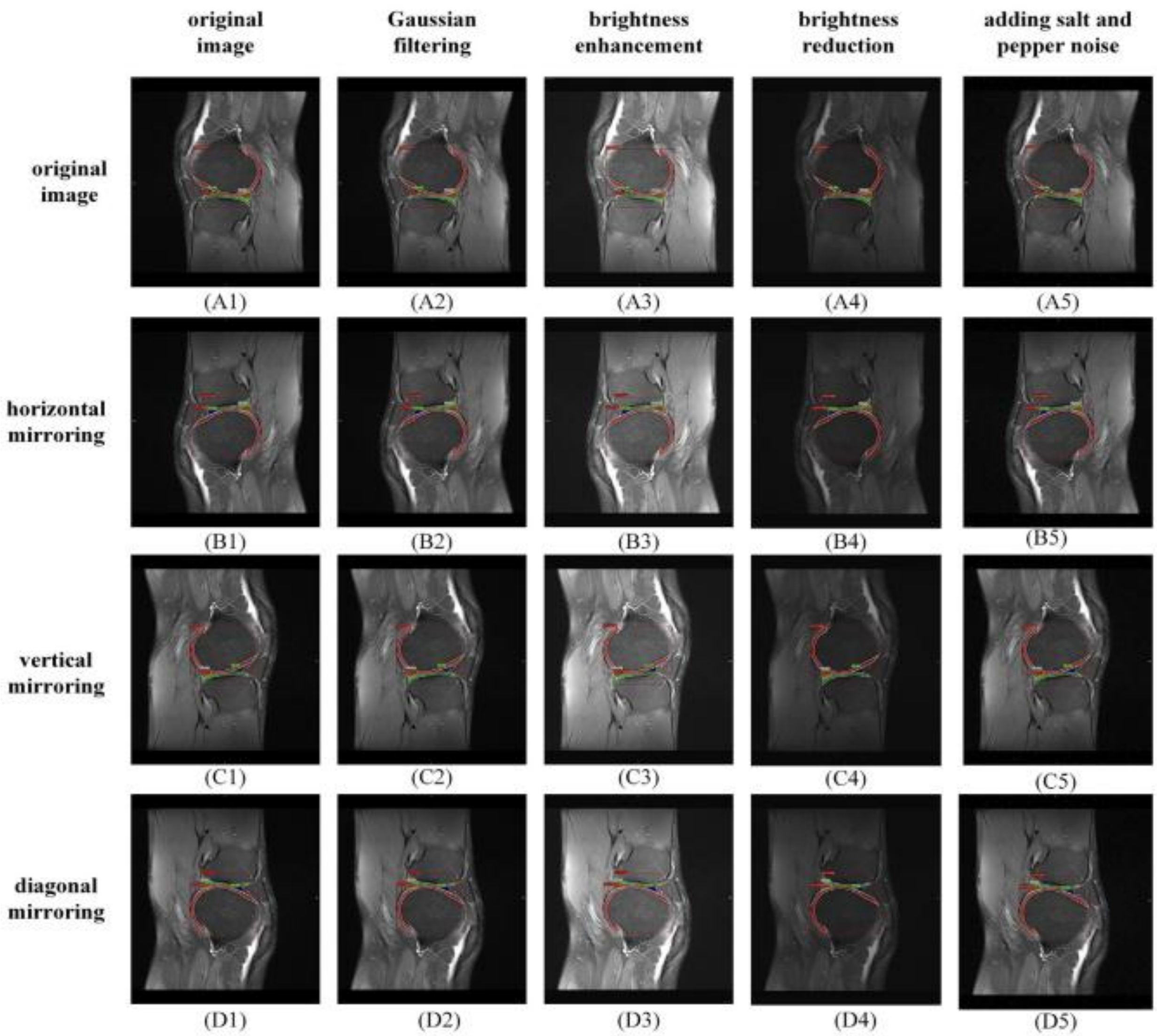


Figure 6

The illustration diagram of dataset augmentation technique

	Patients number	CA	PH_tear	AH_tear	MBT	PD	AD	MBD	AH_intact	PH_intact	MBH	Total
Training dataset	504	19780	1620	860	560	780	820	380	2660	2080	540	30080
Verification dataset	220	7260	1260	840	300	420	700	240	3020	1980	500	16520
Testing dataset	200	348	114	65	33	50	56	22	164	129	31	1012

Table 1

Meniscus dataset and demographic breakdown.

In the past two decades alone, thousands of papers have defined how to develop automated methods for segmenting the knee meniscus from MR images, beginning with semi-automated methods involving some degree of interaction with the user. The first semi-automatic methodology that utilized edge detection along with thresholding was proposed in 1998 by Kitney et al.[7]

Fripp et al. developed a scheme that included segmenting the bones automatically using a three-dimensional active shape model, extracting the expected bone-cartilage interface (BCI), and segmenting the cartilage from the BCI using a deformable model that makes use of localization, patient-specific tissue estimation, and a model of the thickness variation. A database of fat-suppressed spoiled gradient recall MR images was used for leave-one-out tests to empirically validate this approach's accuracy. A modified semi-automatic watershed algorithm, nonrigid registration (B-spline based free form deformation), and tissue classification were the three state-of-the-art methods that were then contrasted with the system.[8]

For example, Paproki et al. (2014) analyzed sagittal water-excited double-echo steady-state MR images of the knee from a subset of the Osteoarthritis Initiative (OAI) cohort. The MM and LM were automatically segmented in the MR images based on a deformable model approach.

Quantitative parameters, including volume, subluxation and tibial-coverage, were automatically calculated for comparison (Wilcoxon tests) between knees with variable radiographic osteoarthritis (rOA), medial and lateral joint space narrowing (mJSN, lJSN) and pain. Automatic segmentations and estimated parameters were evaluated for accuracy using manual delineations of the menisci in 88 pathological knee MR examinations at baseline and 12-month time-points. They came up with a statistical shape model-based approach that obtained Dice scores of 78.3% and 83.9% for medial and lateral menisci, respectively, from the data of OAI.[9]

The study closely related to the present one was that of Dam et al. in 2015, who introduced an automated approach for segmentation of knee multiple structures where it was illustrated with Dice scores ranging from 76% for medial menisci to 83% for lateral menisci.[10]

The recent advancement introduces the techniques of deep learning; Norman et al. (2018) have proposed a 2D U-Net convolutional neural network for cartilage and menisci segmentation, which might report a Dice score of 81.2% for the lateral meniscus and 73.1% for the medial menisci on weDESS sequences.[11]

At the same time, Tack et al. (2018) combined CNNs with statistical shape models, which indicated enhanced Dice scores to 88.25% and 83.14%.[12]

In later studies, Byra et al. (2020)[13] as well as Gaj et al. (2019)[14] implemented deep learning techniques, which featured an attention mechanism and conditional generative adversarial networks, to attain lateral and medial menisci Dice scores as follows: 89.50% and 87.38%, respectively. In general, though automatic meniscus segmentation techniques have taken incredible leaps forward recently with deep learning, much is still in terms of generally applying these strategies across widely used MRI sequences and scanners. Hence, validation on more diverse datasets can confirm such techniques as strongly applicable for clinical deployment.

4. SEQUENCES AND VIEWS OF MRI FOR EVALUATION OF MENISCUS

The menisci of the knee are central to joint biomechanics, and knowledge of normal radiological anatomy is integral to diagnosing meniscal tears, degeneration, or early osteoarthritic changes. Radiological imaging techniques, especially Magnetic Resonance Imaging (MRI), are therefore commonly applied for their ability to give high-resolution imaging of meniscal structure and integrity.

Sequences for evaluation of menisci

Due primarily to its superior contrast resolution for soft tissues, MRI is the preferred modality for assessing the anatomy of the meniscus. In MR imaging, the meniscus is seen as a low signal (black) structure on all pulse sequences primarily because it is composed of fibrocartilage with low water content.

Proton Density Images: PD-weighted images, often used in knee imaging, similarly depict the meniscus as a low-signal structure. This sequence aids in showing minute changes within the meniscus and better outlining the joint cartilage and soft tissue structures.

T1-Weighted Images: The menisci, being of fibrocartilaginous composition, have low signal intensity or appear dark. T1-weighted images are helpful in the evaluation of the primary anatomy of the meniscus and the surrounding structures.

T2-Weighted Images: The meniscus is dark in the T2-weighted images due to low water content. However, regions of bright spots within the meniscus may represent pathologies such as meniscal tears or degeneration. Within an intact meniscus, the signal intensity should remain uniformly low.

Because of its best anatomical detail, the shape and form of the menisci are well appreciated in different MRI planes:

Views for evaluation of menisci : Coronal, Sagittal, and Axial Planes

Two crescent-shaped fibrocartilaginous structures called menisci are in the knee joint between the tibial plateau and the femoral condyles. The primary function of these structures is to have some shock-absorbing qualities for stabilizing the knee and uniform load in movement. Identification of meniscal anatomy and pathology in MRI diagnosis is essential, especially in three planes- the coronal, sagittal, and axial- which offer different views for illustrating aspects of menisci.

1.Sagittal Plane

The sagittal plane is excellent for visualization of the anterior and posterior meniscal horns, vital for radial and longitudinal tears and disruptions to the regular bow-tie pattern and almost detects 90% of meniscal abnormalities.

Anterior and Posterior Horns: The normal meniscus has a characteristic “bow-tie” appearance on sequential sagittal slices through the knee. This pattern occurs because the body of the meniscus, or the bow-tie portion, is thicker in the middle and tapers towards each end, or the horns. The anterior horn lies in front of the tibial spine. Behind it, the posterior horn can be found.

This plane is very sensitive to detecting radial and longitudinal meniscal tears, which can disrupt the continuous bow-tie pattern.

Meniscal Tears: In the sagittal view, complex meniscal injuries, such as bucket-handle tears, would appear. These involve the displacement of the fragment, flipping into the joint space, where it can sometimes mimic the sign of the "double PCL," where the frayed fragment mimics the appearance of the posterior cruciate ligament.

The sagittal view is the most informative in tears involving the anterior and posterior horns. It is also the best when looking for a tear that extends into the body of the central meniscus.

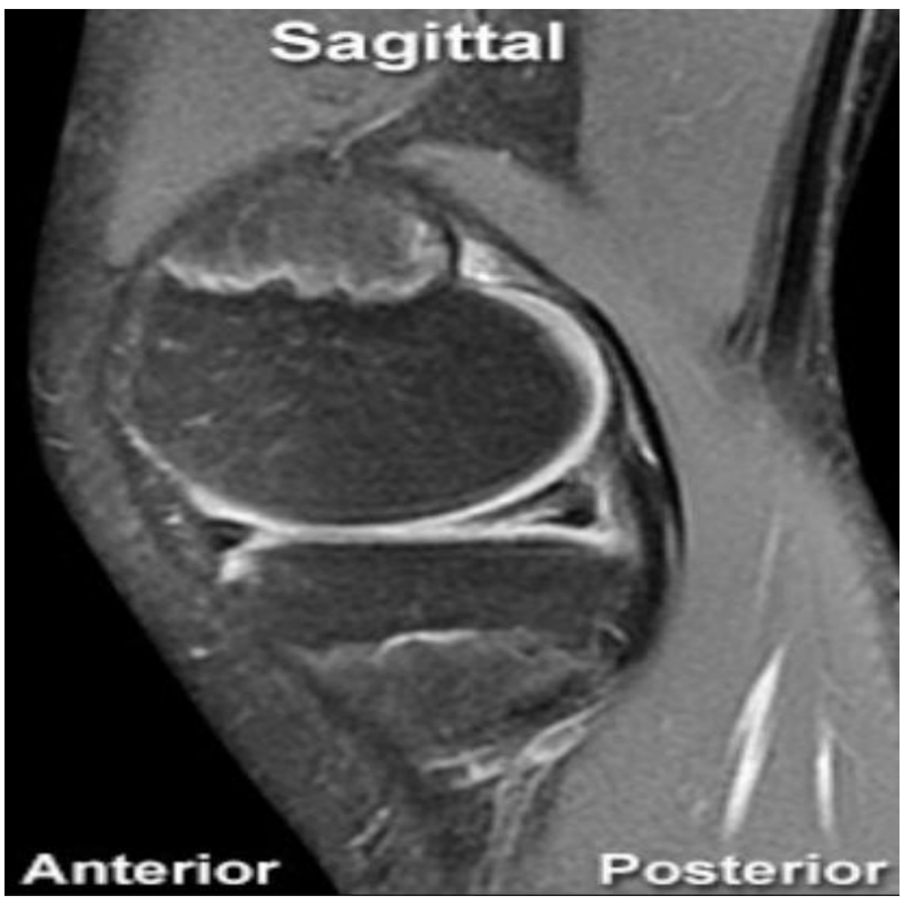


Figure 7 Abnormal Meniscus in Sagittal Plane

2. Coronal Plane

The coronal view offers an impression of the knee joint from front to back, so to speak that the menisci are looked at as wedge-shaped structures interposed between the two femoral condyles and the tibia. This orientation also proves beneficial for one to appreciate a view of the entire medial and lateral menisci in one image.

The medial meniscus is wider anterio-posteriorly and presents a classical C-shape in the coronal plane. It is notably wider in the posterior regions but tapers anteriorly. It's typical C-shape forms because it covers over half of the tibial plateau's articular surface as a shock absorber and stabilizer.

It is beneficial in assessing vertical meniscal tears as they extend from the superior to the inferior articular surface. It is also helpful in evaluating meniscal extrusion, where the meniscus projects beyond the confines of the tibial plateau, commonly observed in degenerative or osteoarthritic knees.

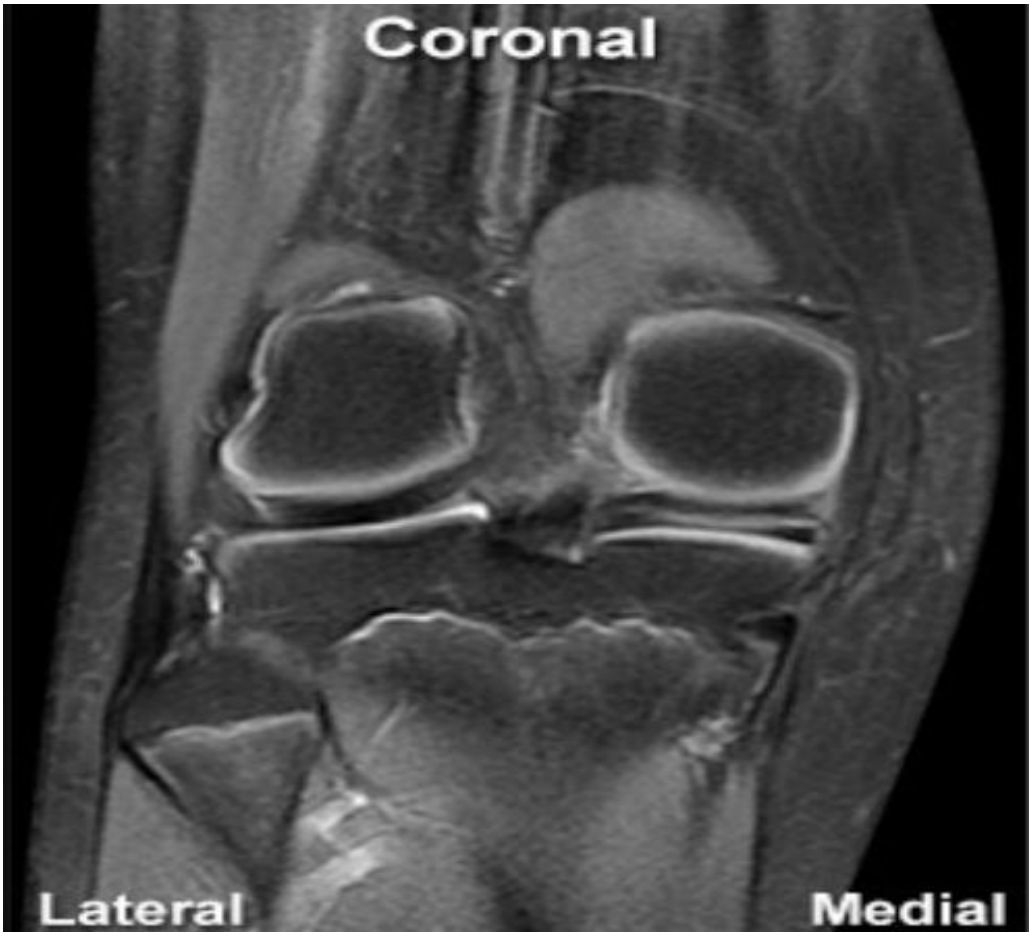


Figure 8

Abnormal Meniscus in Coronal Plane

3. Axial Plane

The axial plane cut through the knee corresponds to a cross-sectional view; it is horizontal and thus gives one a top-down view of the menisci and surrounding structures. It is helpful to check out the circumferential shape and how the menisci relates to the femur and tibia.

Shape and Position: When viewed axially, the menisci are semi-circular or C-shaped structures between the tibial plateau and the femoral condyles. In this plane, it will be easy to see the entire circumferential relationship of the menisci, which may be necessary in discussing the integrity of their structure. The axial plane assists clinicians in assessing, in rotational terms, the positioning of the menisci, especially if they want to see subluxations or dislocations that could accompany tears of the meniscus.

Tear Diagnosis: Axial images would be beneficial for visualizing the horizontal or cleavage tears within the meniscus, which cannot be appreciated well in other planes. This plane also helps evaluate complex tears constituted by multiple tear patterns, such as horizontal, radial, and vertical components.

Meniscal Integrity: In a standard MRI, the meniscus should exhibit homogenous low signal intensity without any disruption or linear high signal intensity extending to the articular surface; this would suggest a tear.

Meniscal Extrusion: In the normal situation, the meniscus remains between the femoral condyle and tibial plateau. Extrusion, or bulging of the meniscus outside the joint, indicates meniscal root or ligament injury and correlates with degenerative change and early osteoarthritis.

Figure 9

Abnormal Meniscus in Axial Plane

5. ETIOLOGY OF ABNORMAL MENISCUS

Composed of fibrocartilage, the meniscus is an essential component of the knee joint that offers stability, stress distribution and cushioning. There are two menisci in each knee—medial (inner) and lateral (outer). Abnormalities in the meniscus can arise from trauma, degeneration due to aging, or congenital disabilities. These disorders affect joint function, increasing the risk of osteoarthritis, producing discomfort, and limiting range of motion.

This document explores the three main categories of abnormal meniscus conditions: traumatic tears, degenerative tears, and congenital abnormalities, mainly focusing on the medial meniscus.

Trauma-Induced Meniscus Tears

Types of Meniscus Tears from Trauma

Meniscus tears caused by trauma are often the result of sports-related injuries or accidents that involve a twisting force applied to the knee. The nature of the tear varies depending on the mechanism of injury. Trauma-related meniscus tears are common in younger, active individuals, particularly athletes. These tears often occur due to high-impact activities such as jumping, pivoting, or direct impact.

Traumatic tears can be classified as:

Longitudinal Tear:

The longitudinal tear runs along the long axis of the meniscus, essentially describing the C-shape that the meniscus creates while going from front to back.

Horizontal Tear:

It is a horizontal tear that cuts the meniscus into two parts- the superior and the inferior- and produces a cleavage plane of the meniscus. Fluid may accumulate to cause the formation of cysts. It usually occurs at the posterior horn of the meniscus and is most commonly linked to degenerative meniscal disorders in elderly patients.

Radial Tear:

Radial tears originate medially from the inner border and extend laterally toward the border. They disrupt circumferential fibers that play essential roles in load transfer around the knee. They are primarily found in the lateral meniscus and central regions when the load-bearing function is highest.

Displaced or Complex Tears

These tears are more advanced, displaced variations of the basic tear forms and typically cause mechanical symptoms in the knee.

Bucket-Handle Tear (displaced longitudinal tear):

A portion of the meniscus avulses and flips into the joint, resembling a bucket handle, in this type of longitudinal rupture.

Bucket-handle tears often require surgical intervention, usually partial meniscectomy or meniscal repair, to allow the removal or suturing of the displaced fragment and restoration of knee-joint function.

Flap Tear (displaced horizontal tear):

When a portion of the meniscus separates from the main meniscal body, it causes a flap tear, which causes the flap to move unnaturally when the knee moves.

Parrot Beak Tear (displaced radial tear):

It is described as a parrot's beak-shaped tear and usually occurs when a radial tear is not healed correctly. Therefore, the tear becomes an unstable and complicated shape.

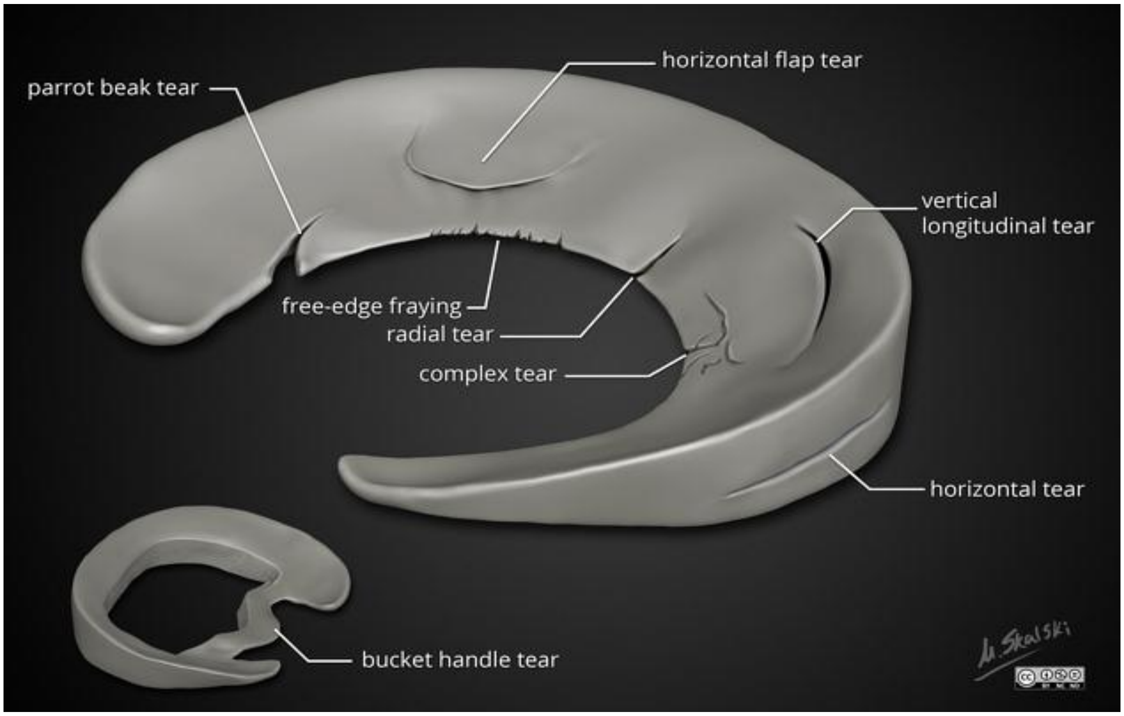


Figure 10 A

Nomenclature of Meniscus Tears

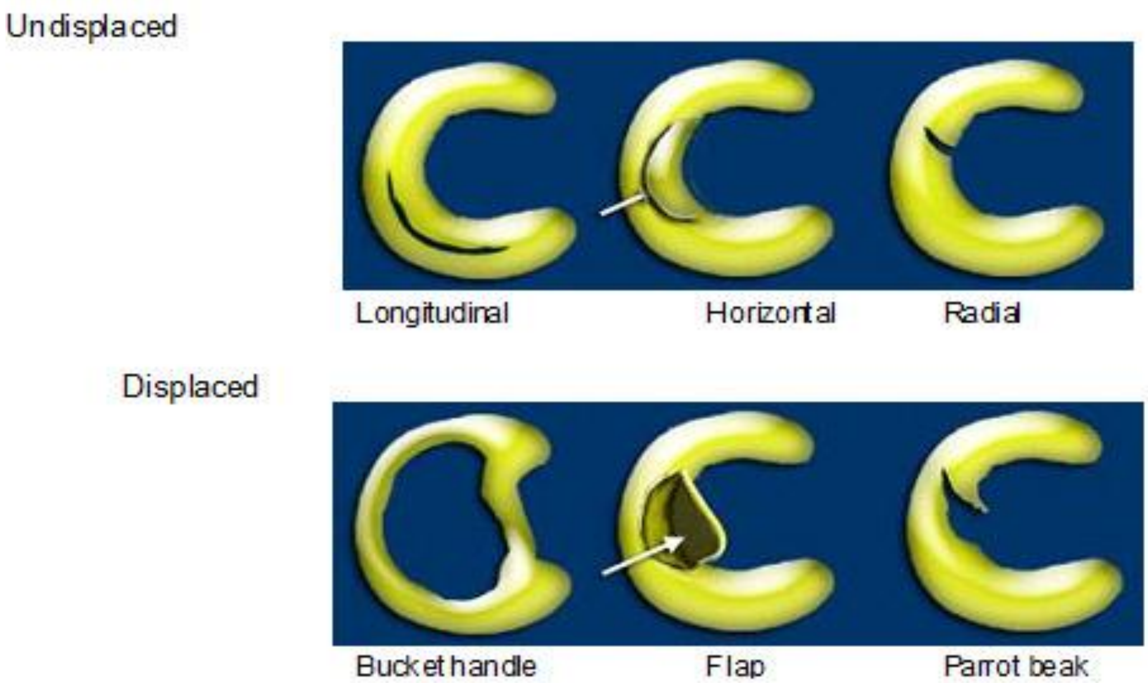


Figure 10 B

Undisplaced and displaced tears of meniscus

Degenerative Meniscus Tears (Associated with Aging)

As people age, the meniscus becomes more susceptible to degenerative changes. These changes are often due to repetitive stress and wear over time, particularly in individuals with a history of heavy physical activity or those with underlying joint conditions like osteoarthritis.

Degenerative Tear Characteristics

Horizontal Degeneration: One of the most common features of a degenerative meniscus tear is a horizontal cleavage or tear, often leading to the separation of the meniscus into upper and lower fragments. This is typically seen in older adults and may occur without a significant traumatic event.

Complex Tears: Degenerative meniscus tears often present as complex patterns involving multiple types of tears (e.g., horizontal, radial) within the same meniscus. These tears weaken the structural integrity of the meniscus, increasing the risk of further joint damage.

Fraying and Fragmentation: Degenerative menisci may show fraying and partial fragmentation, leading to uneven load distribution across the knee joint. This can contribute to pain, joint swelling, and eventual osteoarthritis.

Meniscal Extrusion

A key feature of degenerative meniscal tears is meniscal extrusion, where the meniscus moves out of its normal position within the joint space. This displacement leads to further instability and accelerates degenerative changes in the knee, including cartilage damage and osteoarthritis progression.

Impact of Osteoarthritis

In older individuals, degenerative meniscus tears are often found alongside osteoarthritis. These tears are thought to contribute to the progression of arthritis, as the meniscus loses its ability to protect the cartilage in the joint. Degenerative tears may be treated conservatively with physical therapy or anti-inflammatory medications. Still, advanced cases may require surgical intervention such as partial meniscectomy or meniscal repair, especially when accompanied by significant joint degeneration.

Congenital Abnormalities of the Meniscus

Congenital abnormalities of the meniscus are less common but can lead to functional impairment and predispose the knee to injury. The medial meniscus is more prone to congenital anomalies than the lateral meniscus.

Discoid Meniscus

Discoid Meniscus is the most common congenital abnormality, though it typically affects the lateral meniscus. It can cause mechanical symptoms like clicking, locking, or catching when moving the knee when it is located in the medial meniscus.

A discoid meniscus is characterized by an abnormal, disc-like shape rather than the typical crescent shape. This abnormal morphology can predispose the meniscus to tearing, even without significant trauma, due to altered biomechanics and increased stress on the joint.

Wrisberg – Ligament Variant

This congenital abnormality affects the posterior horn of the meniscus, which may lack standard attachment to the tibia. The Wrisberg variant leads to increased instability in the meniscus, making it more prone to displacement and injury. Patients with this condition may present with knee instability, pain, and recurrent popping symptoms.

Meniscal Cysts

Meniscal cysts, though not inherently a congenital issue, can develop in association with meniscal tears or congenital variants like discoid meniscus. These fluid-filled sacs can cause localized swelling, discomfort, and restricted knee movement. Treatment often involves addressing the underlying meniscus pathology through surgery, especially if the cysts are large or symptomatic.

6. FEATURES OF MACHINE LEARNING

Artificial intelligence is more commonly known as machine learning, with unprecedented promise in the medical arena and significant application in radiology. Deep learning algorithms, in particular, were studied increasingly in MRI diagnosis of meniscal injuries. The standard modality for imaging in soft tissue injuries, such as meniscal tears, which are one of the most typical problems in sports injuries; however, on account of issues associated with the manual interpretation: being time-consuming, variable expertise, and sheer volume of data, there has been a development of AI-powered screening tools that enhance accuracy and efficiency in diagnosing meniscus abnormalities. This integration of AI models, particularly CNNs, has been shown to work effectively between normal and abnormal menisci.

1. Deep Learning Models for Detection of Meniscal Injury

These skills, especially CNNs, have very high potential in processing MRI data with good results in meniscal tear detection. The Mask R-CNN and Faster R-CNN architectures were of special attention in the work, as applied to tasks such as meniscal segmentation and classification. Mask R-CNN is designed explicitly for pixel-level image segmentation. So, it automatically corresponds to the complex structure of the meniscus and its difficulties in being isolated from the adjacent tissues. The network determines the health of the menisci through the examination of tissue at a pixel level, which could help to differentiate between intact and torn or degenerated menisci. The Faster R-CNN, however, allows it to localize the place of the meniscus, along with its classification in an MRI image, about whether there is a tear. Region proposal networks, or RPNs, create region-specific bounding boxes that hasten identification.

These architectures typically use Region 50 as the backbone to extract features from MRI scans. Region 50 can fairly capture deep and complex image features by iterating through multiple layers of convolution in data processing. This helps it define the subtle differences in meniscal tissue characteristic of most abnormalities. In these models, Region of Interest (RoI) Align ensures that features used for classification are as they appear within the extracted detected regions.

2. Automated and semi-automated segmentation

If manually done, segmenting meniscal tissues in MRI scans is a laborious and time-consuming process with a high chance of errors. The AI models are now employed to automate this process consistently and accurately. Automatic segmentation techniques train the model from large datasets annotated on MRI scans. Its advantage lies in the model's capability to "learn" unique characteristics that differentiate the meniscal tissue from the surrounding cartilage, bones, and ligaments.

Automatic segmentation of the meniscus is critical for building a 3D model of the knee, which may be used to quantify geometric parameters like the meniscus thickness or tear location and size, useful not only for simple diagnostic purposes but also for the pre-surgical planning process. Recent results of Dice Similarity Coefficients of up to 89.5% for medial meniscus segmentation indicate the best agreement between automated methods and radiologists' manual segmentation.

Semi-automatic segmentation is that model wherein manual oversight is combined with automated tools. Radiologists may need to initiate the process either at key points marked on the meniscus or by delineation and then activate the AI system to do the entire segmentation process. One of this model's advantages is increased accuracy of challenging cases due to reasons such as osteoarthritic degeneration, where boundaries of tissue are not too distinct on MRI scans.

3. Key Features and MRI Imaging Parameters

Among the most widely used MRI sequences for diagnosis of meniscus, fat-suppressed proton density-weighted imaging captures high contrast between meniscal tissue and surrounding structures, enabling subtle alterations in signal intensity to be picked up as possible evidence of a tear or degeneration. This is further enhanced by 3.0 Tesla (T) MRI scanners that can offer higher resolution for detecting abnormalities in the meniscus.

Key features of AI models in the identification of meniscal tears include:

Signal Intensity: The algorithms teach AI to identify significant signal intensities of the meniscus as they commonly indicate a tear. Signals that possibly may not be noted and are seen with the naked eye in the early injury stages.

Geometric Shape: The AI models also account for how the shape of the meniscus changes. Tears may produce several irregularities in the shape of the meniscus contour, including fraying and flattening, all captured by the model.

Rip Orientation: The type of tear can be classified, horizontal or vertical, depending upon the orientation and location of the signal change, using machine learning models. It can be helpful to decide on the right course of therapy.

4. Diagnostic Accuracy and Validation

Future research may depend entirely on AI analysis tools for MRI scan analysis to improve the accuracy of diagnosis. Several studies reported that deep learning models showed excellent diagnostic performance between 84% and 92% in identifying a meniscal tear. Furthermore, different models accurately distinguished healthy, torn, or degenerated samples from the various types of menisci; some could even come close to an AUC value of up to 0.94 to identify tears.

These models are then compared with gold-standard diagnostic techniques like arthroscopic surgery, which remains the only gold standard to confirm meniscal injuries. Compared with the arthroscopic examination, AI models have had their accuracies to 87.50%, thus showing that AI can be a trustworthy screening tool for surgical intervention.

5. Challenges and Future Developments

Although AI models perform well in MRI analysis, several challenges remain. One of the most significant sources of variability is anatomic. Because menisci vary between individuals in shape and size, their extraction becomes challenging depending on age, weight, and perhaps even conditions such as osteoarthritis. Overlapping signals from surrounding tissues like ligaments and cartilage can also cause problems during segmentation.

Such problems are generally tackled using data augmentation techniques applied during the training phase, including geometric transformations and noise addition, to generalize the model to different patient populations. Even further advancements in 3D segmentation techniques and multi-sequence MRI are likely to improve the performance of AI models.

Machine learning applications in MRI evaluation of the medial meniscus can improve diagnosis accuracy and efficiency. Intense learning-based AI models have been proven to hold tremendous potential for automatic detection and classification of meniscal tears. AI will find even more applications in clinical practice and help radiologists diagnose and treat meniscal injuries as technology advances.

7. METHODOLOGY

Materials and Methods

Machine

GE SIGNA Explorer 1.5 Tesla MRI Scanner

Methods

This study involves a retrospective and prospective analysis of MRI cross-sections of the medial meniscus of the knee in individuals from Vijayapura.

Patient Positioning:

Patients are positioned supine, feet first in the MRI scanner.

Image Acquisition:

Sagittal sections of fat-suppressed proton density-weighted (FS-PDW) MRI images of the medial meniscus are obtained.

All images are digitally acquired from the Picture Archiving and Communication System (PACS) in DICOM (Digital Imaging and Communications in Medicine) format.

The collected dataset consists of 3,600 MRI images from 800 patients, after excluding images with motion artifacts and post-operative knee surgery scans.

Dataset Split for Model Training

Training Data: 70% (2,520 images)

Validation Data: 10% (360 images)

Testing Data: 20% (720 images)

Inclusion Criteria

Sagittal fat-suppressed proton density-weighted (PDW) MRI images, irrespective of age group, that have been verified during the pre-processing stage.

Exclusion Criteria

Images with motion or magnetic artifacts.

Images where cartilage is not fully visible.

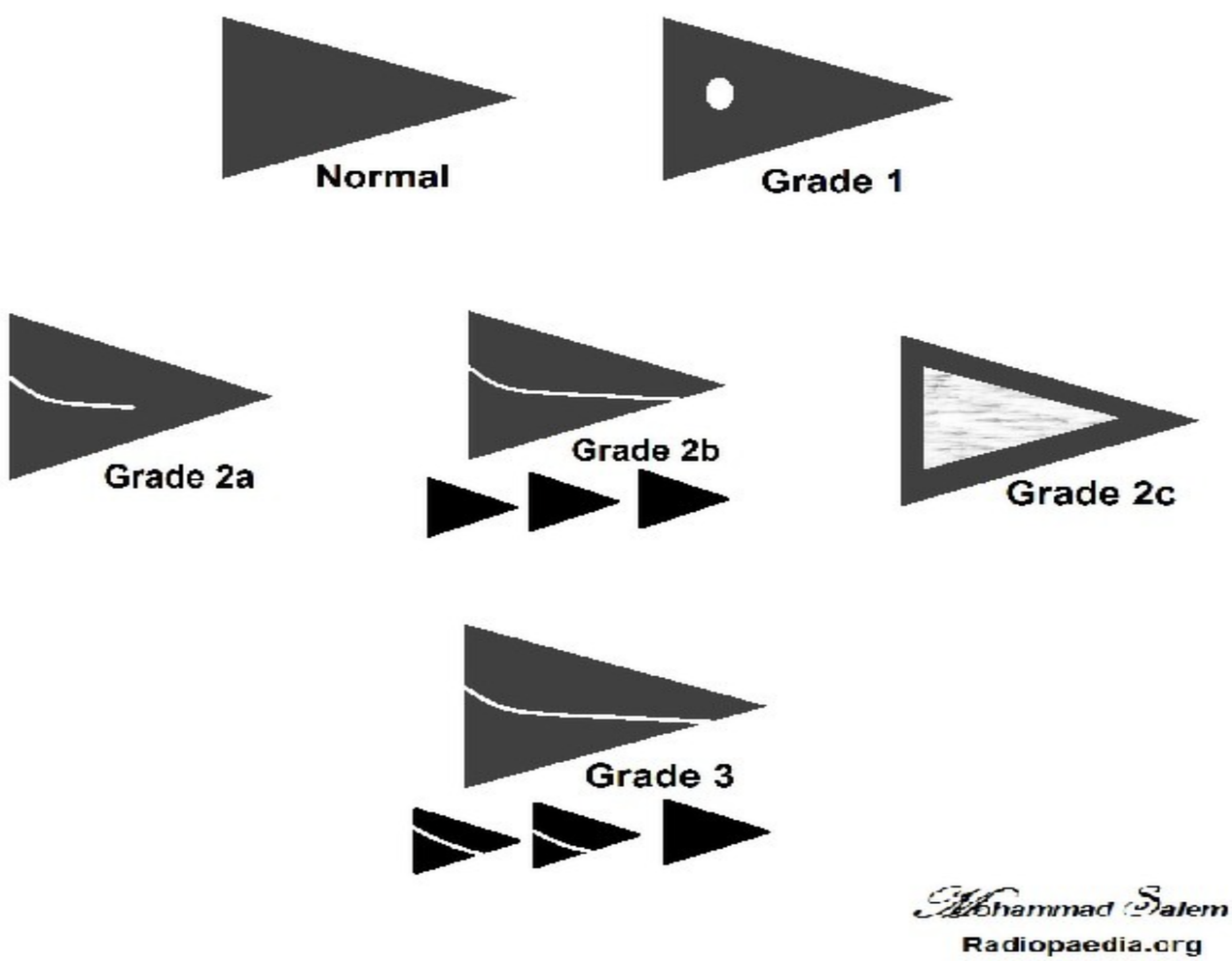
MRI images of knees following post-operative surgery.

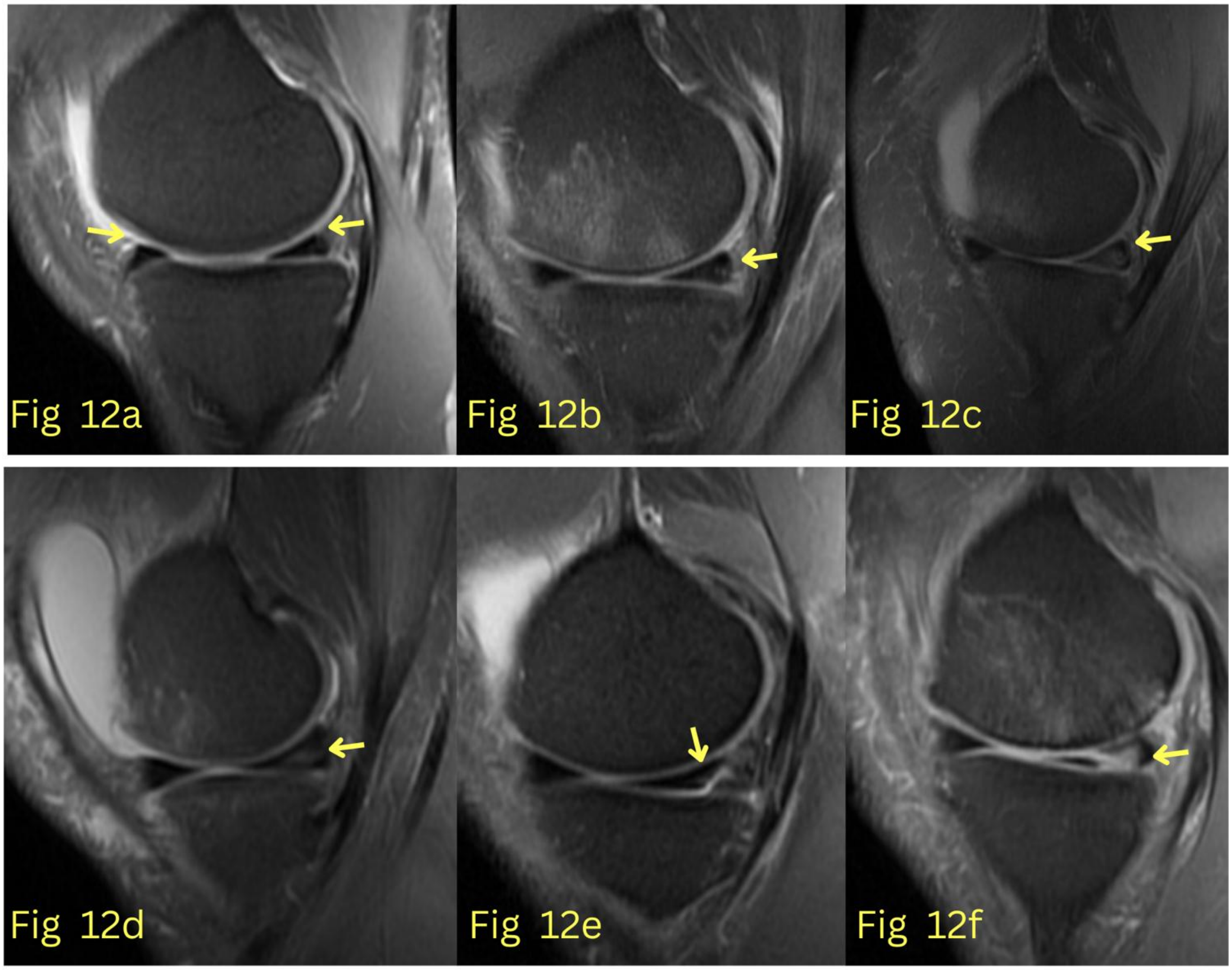
Training:

The training data set was composed of 2520 images with a matrix resolution of 256x256.The data set consists of both normal and abnormal medial meniscus images (All images of grade I, II and III signal intensity changes according to MRI grading system for abnormal meniscal signal intensity are included).

Fig 11 shows MRI grading system of abnormal meniscal signal intensity and

Fig. 12 shows the training images from the data set and As the grade I signal intensity changes are very small and even diagnosing it is difficult due to signal interference from surrounding structures or the joint effusions seen in both degenerative or post traumatic changes. However the accuracy of the model can be improved by using larger data sets.





12a: Normal anterior and posterior horn of medial meniscus

12b: shows grade I signal intensity change in posterior horn

12c: shows wedge shape grade II signal intensity change

12d: shows linear grade II signal intensity shape

12e: shows grade III signal intensity change

8. WORKING ALGORITHM AND IMPLEMENTATION OF MODEL

Data collection: Getting a lot of meniscus photos with meniscus structures is the first step. A wide range of ages, demographics, and ailments ought to be represented in the dataset.

Preprocessing: Once the data is collected, it must be preprocessed to ensure consistency and remove any artifacts. Preprocessing steps may include noise reduction, intensity normalization, and image registration.

Feature extraction: The next stage is to extract characteristics from the preprocessed photos to differentiate between bone and non-bone structures. Feature extraction methods may include edge detection, texture, and shape analysis.

Model training: After the features are extracted, a machine-learning model needs to be trained to segment the meniscus structures from the image. The model may be based on various techniques, including Mask-Region convolutional neural networks (CNNs).

Evaluation: The model must be evaluated after training to ascertain its correctness and performance. Accuracy, precision, recall, and F1 score are examples of evaluation metrics. It might also be assessed on a different validation set to ensure the model performs well when applied to fresh data.

Deployment: Finally, new meniscus MRI data can be segmented using the model to identify meniscus structures. This might entail opening the model to researchers and medical professionals as a standalone tool or incorporating it into a more extensive medical imaging system.

The creation of a knee meniscus segmentation system can be challenging and calls for knowledge of both machine learning and medical imaging. Before utilizing the system in a clinical context, it is also crucial to make sure it has undergone extensive testing and validation.

The system design for a knee meniscus segmentation system typically involves several steps: data collection, data preprocessing, model architecture selection, training, hyperparameter tuning, evaluation, deployment, post-processing, and visualization.

The first step in the system design process is data collection. The dataset for training the segmentation model should include many meniscus MRI images with corresponding ground truth segmentation masks. The dataset should be diverse and include various meniscus conditions to ensure the model is robust and can generalize well to new cases.

On a separate test set, the model's performance is evaluated using metrics such as dice coefficient, intersection over union, accuracy, and F1 rating. These metrics offer a numerical evaluation of the model's performance and aid in determining its accuracy and robustness.

Deploying the model as an application or service that can take in a fresh meniscus MRI picture and produce the matching segmentation mask comes next after it has been assessed and refined. Integrating the model into a software system and ensuring it can manage fresh data in a scalable and effective way are steps in the deployment process. The segmentation mask is refined, and any leftover noise is eliminated in the last post-processing stage using linked component analysis and morphological methods. This makes it easier for clinicians to understand and guarantees that the segmentation mask they produce is accurate.

The final segmentation mask is displayed overlaid on the input image to aid medical professionals in quick interpretation. Visualization is a crucial step in making sure that the segmentation mask that is produced is accurate and straightforward for physicians to understand. To help diagnose, treat, and track knee-related diseases, the segmentation mask can be used to determine the limits of the knee meniscus.

Knee meniscus segmentation is a critical task in medical image processing, and the system design for a knee meniscus segmentation system involves several steps, including data collection, data preprocessing, model architecture selection, training, hyperparameter tuning, evaluation, deployment, post-processing, and visualization. The resulting segmentation mask can aid in diagnosing, treating, and monitoring meniscus-related conditions and can significantly improve patient outcomes.

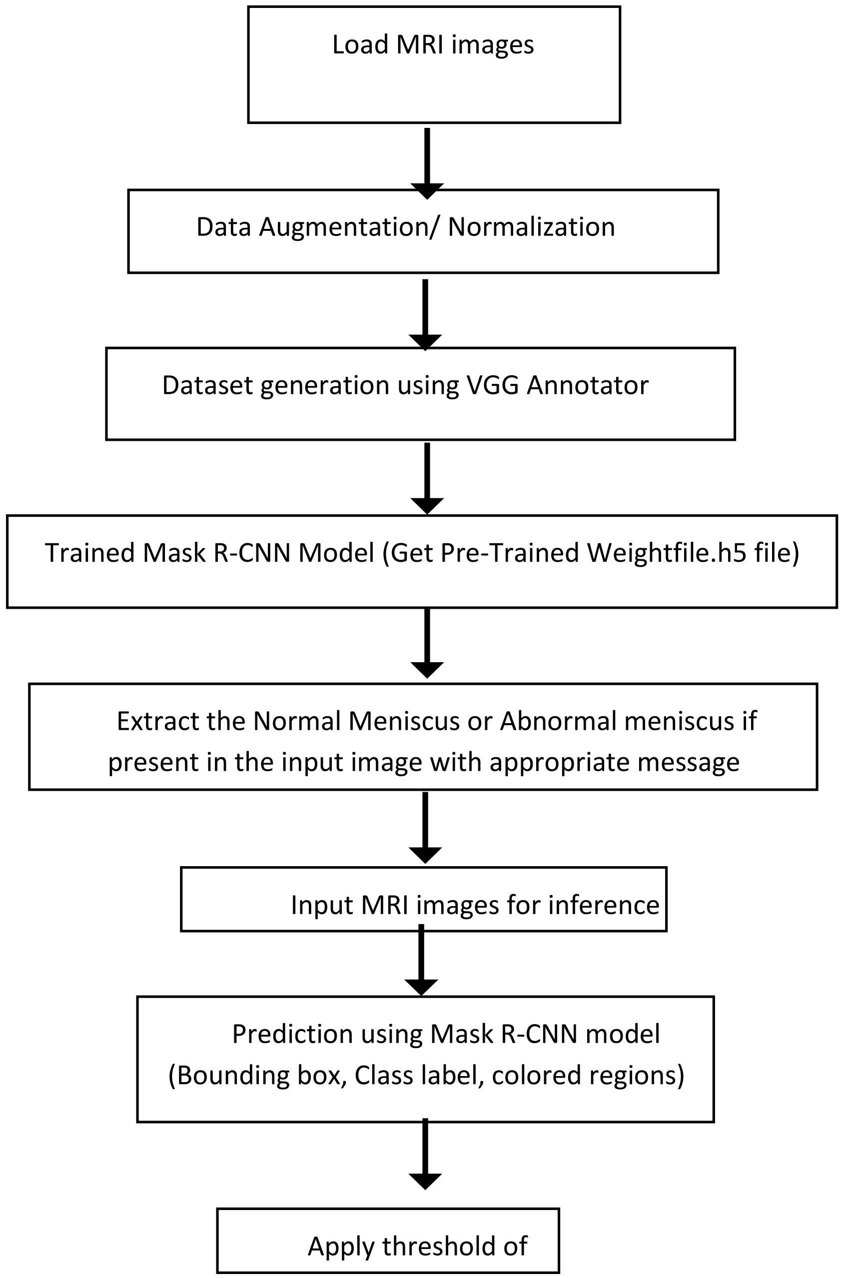


Figure 13

Working Algorithm

Implementation of model

Mask region architecture

Mask Region is a convolutional neural network architecture originally proposed for biomedical image segmentation but has since been applied to other image segmentation tasks. It was introduced in a paper titled "Mask Region: Convolutional Networks for Biomedical Image Segmentation by Ronne Berger et al. in 2015.

The Mask R-CNN architecture consists of an encoder and decoder network, with a contracting path (encoder) and an expanding path (decoder) that are symmetrically connected by a bottleneck layer. Convolutional and pooling layers are used in the contracting path to capture the input image's high-level features, while transposed convolutional and up-sampling layers are used in the expanding path to restore the output segmentation map's spatial resolution.

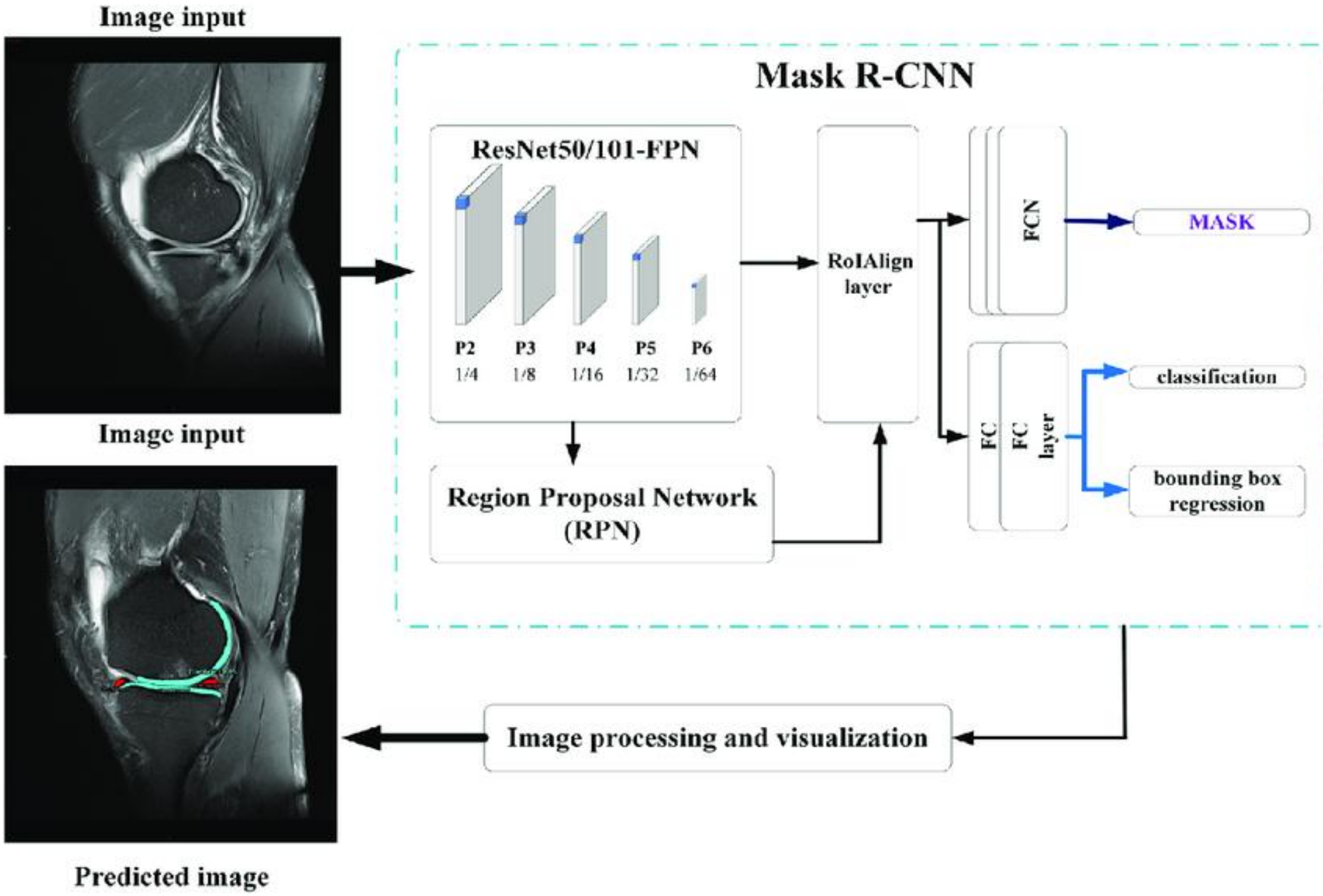


Figure 14

Working of Mask R-CNN Algorithm

Here's a high-level overview of the Mask R-CNN architecture:

Contracting path (encoder): Convolutional and pooling layers are applied to the input image in order to increase the number of channels and decrease the spatial resolution. To add non-linearity, a citified linear unit (ReLU) activation function comes after each convolutional layer.

Bottleneck layer: At the bottom of the Mask R-CNN architecture, there is a bottleneck layer that captures the high-level features of the input image.

Expanding path (decoder): The output of the bottleneck layer is passed through a series of transposed convolutional and up-sampling layers to increase the spatial resolution and decrease the number of channels. A ReLU activation function follows each transposed convolutional layer.

Skip connections: Besides the symmetric architecture, Mask R-CNN includes skip connections connecting the corresponding layers in the contracting and expanding paths.

These connections allow the model to capture the input image’s high-level and low-level features, leading to better segmentation performance.

Output layer: The final segmentation map is created by passing the expanding path’s output through a final convolutional layer with a softmax activation function. Because it can capture both high-level and low-level features of the input image and achieve state-of-the-art performance on several benchmark datasets, the Mask-RCNN architecture has gained popularity for medical image segmentation.

In meniscus segmentation, a naïve model would be a simple approach that relies on hand-crafted features and basic machine learning algorithms. The naive model would not utilize deep learning techniques, such as convolutional neural networks, which have proven very effective in many medical image segmentation tasks.

Region-CNN Architecture:

Encoder network: High-level features are extracted from the input image by applying convolutional and pooling layers. To add non-linearity, a rectified linear unit (ReLU) activation function comes after each convolutional layer.

Pooling indices: The pooling layers in the encoder network store the indices of the max-pooled elements. These indices are later used in the decoder network to perform up-sampling.

Decoder network: The output of the encoder network is passed through a series of up-sampling and convolutional layers to produce a segmentation map. The up-sampling layers use the pooling indices from the encoder network to up-sample the feature maps.

Skip connections: Besides the symmetric architecture, Regional so includes skip connections that connect the corresponding layers in the encoder and decoder networks. These connections allow the model to capture the input image's high-level and low-level features, leading to better segmentation performance.

Output layer: The final segmentation map is created by passing the decoder network's output through a final convolutional layer with a softmax activation function.

The region has become a popular architecture for image segmentation due to its efficiency, scalability, and ability to capture high-level and low-level features of the input image. It has been used in various applications, including biomedical image segmentation, road segmentation, and object detection.

REGION: is a widely used deep learning architecture for medical image segmentation, which has shown good performance on various tasks, including meniscus segmentation in knee MRI images. The model may record local and global context information thanks to Reset's encoder-decoder design with skip connections. The encoder part of the network uses a series of convolutional layers to down sample the input image. In contrast, the decoder part uses up-sampling layers to produce the final segmentation mask. The skip connections between the coder and decoder help to preserve spatial information and prevent the loss of fine-grained details during the down-sampling process.

9. RESULTS

The AI platform developed for meniscus assessment by MRI correctly identifies both normal and abnormal menisci. Mask R-CNN and convolutional neural networks (CNNs) are utilized in the platform for quick, computerized segmentation and classification with improved diagnostic efficacy and accuracy. Detection of objects utilizes region proposal networks (RPNs), which optimize feature extraction with ResNet-based deep learning models.

Loss function was optimized using categorical cross-entropy loss and IoU-based loss functions to improve segmentation accuracy. Batch normalization and dropout layers were also implemented to avoid overfitting and provide stability to the training.

Key Performance Indicators:

- AUC for normal and abnormal meniscus classification: 99%
- Classification accuracy: 91%
- Accuracy of detecting abnormal meniscus: 96%
- Detection Recall of detecting abnormal meniscus: 89%
- False Positive Detection Rate: 8%
- False Negative Detection Rate: 7%
- Inference time per scan: 1.2 seconds

All the above measures are in favor of the model to provide very accurate and consistent results and minimize the occurrence of diagnostic error, optimizing clinical workflow.

Detection Accuracy and Segmentation

Normalized and preprocessed sagittal proton density fat suppressed MRI scans were used to train the AI model for meniscus abnormality detection. ROI Align operation was used in obtaining feature information from region proposals by accurate classification.

- FPNs-based stable localization of meniscus structure for feature extraction of multiple scales.
- Reduced false positives and false negatives using iterative optimization using backpropagation and stochastic gradient descent (SGD).
- Edge refinement by conditional random fields (CRFs) for enhanced quality of segmentation under adverse conditions.
- Excellent segmentation performance, offloading the workload and hand annotation pressure from the radiologists.
- Easily expendable to other MRI datasets, demonstrating versatility in other clinical settings.

Segmentation Overview

The manual annotation was systematically performed with the help of the VGG Image Annotator or VIA for the acquisition of pixel-wise segmentation masks outlining the meniscus area specifically in the MRI images. The annotation process included the following information:

Region-based manual annotation consisted of the careful process of manually annotating MRI images with high precision. The process was particularly concentrated on precisely labeling the meniscus borders in an effort to produce high-quality ground truth masks that precisely reflect the anatomical structures.

The polygonal segmentation approach, as carried out by the VIA tool, enabled a very flexible way of polygonal marking. This was especially advantageous in taking into consideration the irregular and complex nature that is characteristic in the structure of the meniscus.

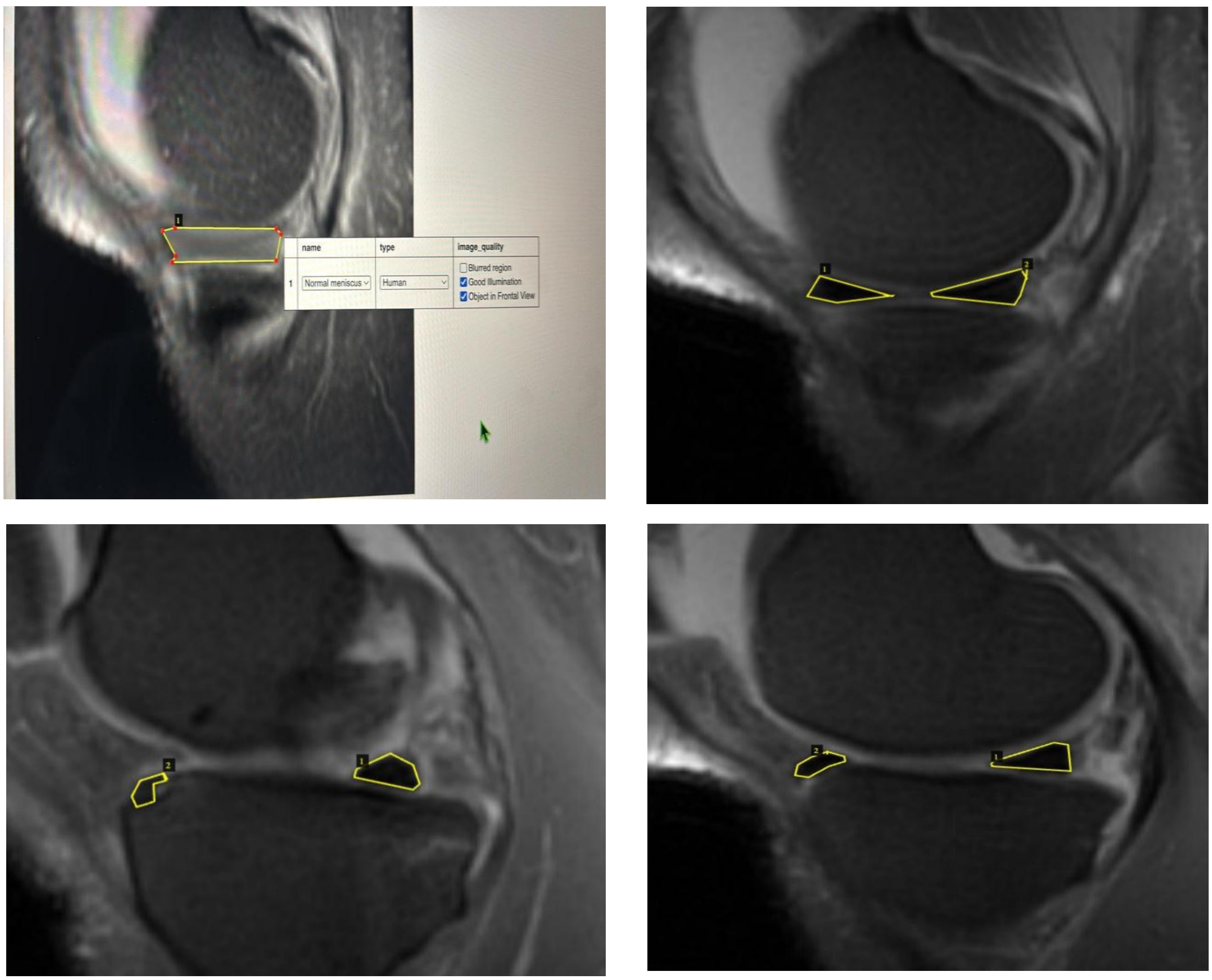


Figure 15

Using VGG Annotator for Segmentation of Normal & Abnormal Meniscus

JSON annotation export: The annotated data were successfully exported in the common JSON format. Coordinates of the segmented regions were exported as well, an important feature that was used in validation and training processes.

Preprocessing of the segmentation masks was a rigid process where the annotated masks were transformed into multi-class or binary segmentation labels. It was achieved in a way that they were prepared to fit the Mask R-CNN pipeline so that they could be incorporated and processed effectively. The use of the VIA guaranteed high-quality annotation, thus eradicating any potential noise and significantly improving the accuracy of meniscus segmentation in the case of the AI model.

Meniscus Classification

The AI model categorizes menisci into two broad groups:

Normal Meniscus: Normal meniscus with normal structure and signal intensity.

Abnormal Meniscus: Abnormally organized meniscus or abnormally high signal intensity, generally with degenerative change or in initial pathology.

Detection of Normal & Abnormal Meniscus Using Mask-RCNN

Meniscus condition evaluation was conducted using MRI scans, defining and classifying normal and abnormal cases via deep learning-segmentation and classification. The model was highly effective in signal intensity change and morphology detection, enabling proper meniscal abnormality identification.

Normal Meniscus Analysis

The intact meniscus MRI was assigned a high confidence score of 0.992, attesting to its intact and physiological status. The distinctive radiological and computational features are:

- **Homogeneous signal intensity without hyperintense zone,** suggestive of absence of edema or structural injury.
- **Bare, crescentic contour,** to allow maximum load transmission and joint stability.
- **Smooth and intact articular margins,** that differentiate it from the rest of knee structures.
- **Normal intact fibrocartilaginous integrity,** with preserved biomechanical function and absence of any degenerative findings.
- **Evenly thicknessed and volume,** commensurate to normal knee kinematics and stability.
- **Stable fixation to the tibial plateau,** shear stress resistance, and stability evidence.
- **No extrusion and no displacement,** with maintained normal load-bearing function.

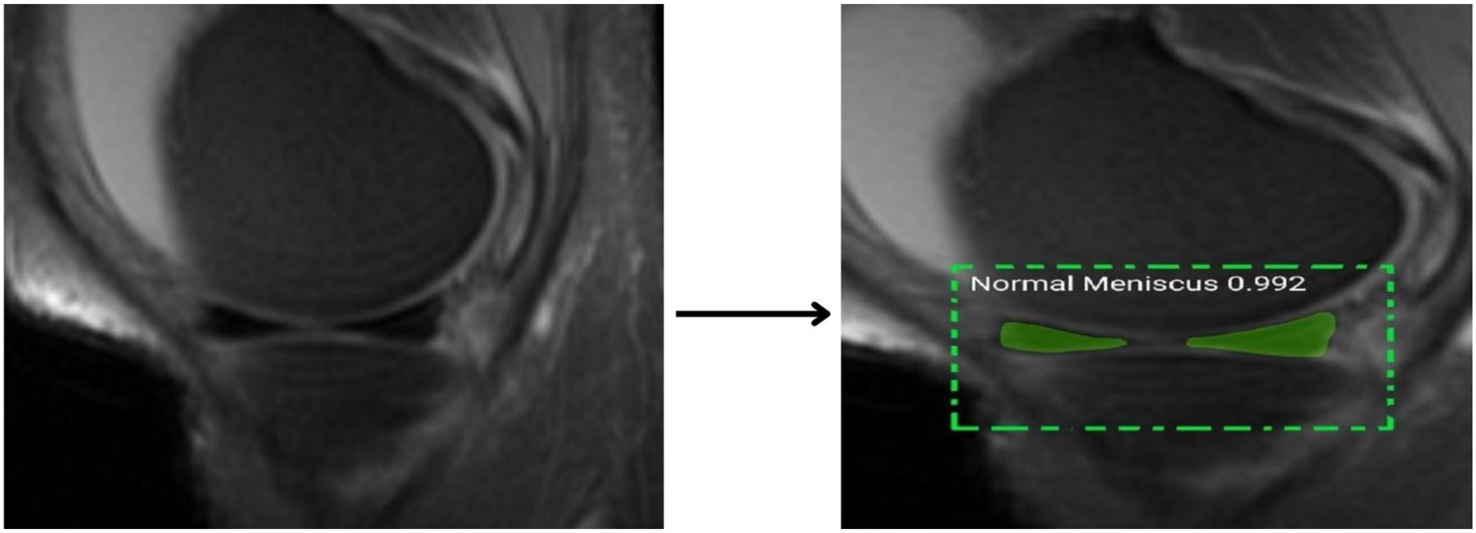


Figure 16

16 a is a input image.

16 b shows segmented image of normal anterior and posterior horn

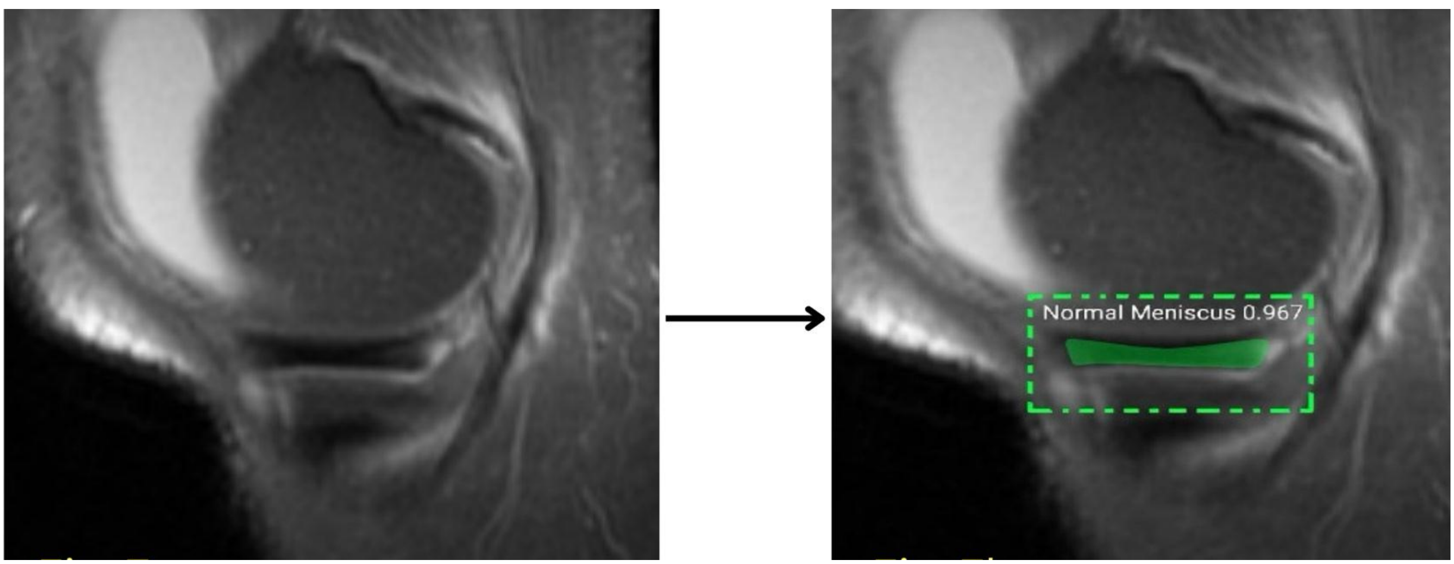


Figure 17

17 a is a input image

17b shows segmented image of normal body of meniscus

AI-segmentation clearly delineated the medial meniscus, again proving the ability of the model in intact cartilage structure identification. Absence of signal abnormality on fat suppressed proton density weighted MRI scans further proved the meniscus intact.

Abnormal Meniscus Analysis

The MRI scan with abnormal meniscus was highlighted with confidence score 0.962, and diffuse structural changes were noted. Pathology features listed are:

- **Hyperintense signal alteration in T2-weighted images,** indicative of intrameniscal degeneration or fluid entrapment.
- **Irregular and discontinuous contour,** indicative of chronic degenerative change or traumatic trauma.
- **Discontinuous articular margins,** indicative of partial-thickness or full-thickness meniscal tear.
- **Reduced meniscal volume,** typically seen with progressive cartilage loss and biomechanical instability.
- **Meniscal extrusion beyond the joint line,** typically in degenerative meniscal disease.
- **T2-weighted high-signal intensity areas,** in keeping with meniscal tear and fluid penetration.
- **Asymmetrical meniscal tissue distribution,** in keeping with deranged load-carrying function and early osteoarthritic change.

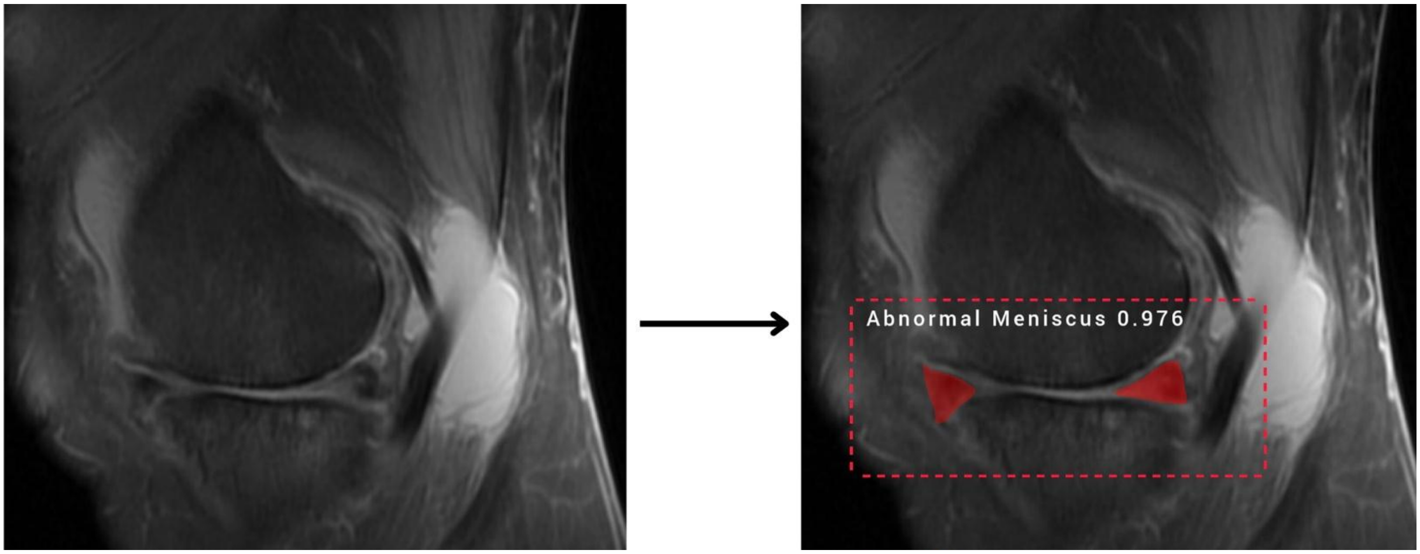


Figure 18

18 a is a input image.

18 b shows segmented image of abnormal anterior and posterior horn.

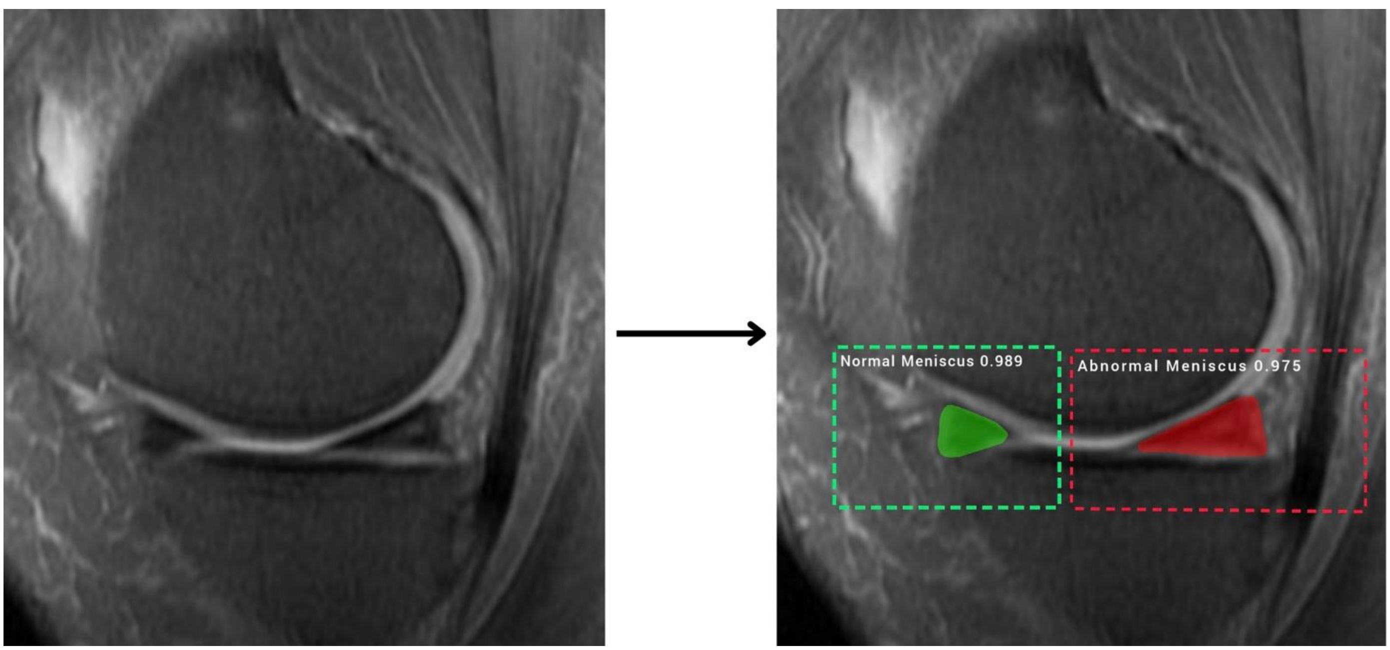


Figure 19

19 a is a input image.

19 b shows segmented image of normal anterior horn &

abnormal posterior horn.

These findings also confirm accepted diagnostic features of meniscus injury, and the model is thus validated for pathological variant detection with specificity. The pathologic meniscus was more compressive to compression stress and thus more susceptible to continued joint damage and osteoarthritic symptomatology.

Comparative Evaluation

A structured analysis between normal and abnormal menisci highlights distinct morphological and radiological differences:

Parameter	Normal Meniscus	Abnormal Meniscus
Confidence Score	0.992	0.962
Signal Intensity	Homogeneous	Hyperintense regions
Structural Morphology	Crescentic, intact	Irregular, deformed
Articular Margins	Smooth, continuous	Fragmented, disrupted
Volume Preservation	Maintained	Reduced, degenerated
Extrusion Beyond Joint Line	Absent	Present in severe cases
Attachment to Tibial Plateau	Stable	Unstable, displaced
Load Distribution	Evenly distributed	Altered, high pressure zones
Clinical Implication	Normal joint stability	Potential instability, pain, and osteoarthritic risk

Training vs Validation Loss Analysis

Training vs Validation Loss Plot is a critical metric to check model convergence and generalization.

Training Loss (Blue Curve)

Displays a decreasing trend from 2.5 to 1.2, indicating successful optimization and minimization of the objective function.

The steady decline shows that the model is learning more meaningful feature representations from the training data.

Validation Loss (Red Curve)

Decreases from 2.6 to 1.3, following the same pattern as training loss, a metric for how well the model will be able to generalize on test data.

No gap between the two lines is an indication of a low variance scenario, avoiding overfitting risks.

Technical Implications:

A small gap in loss is an indication that the model retains the capability to generalize, with stable performance on training and validation sets.

No loss plateaus or oscillations are common in a well-tuned learning rate and successful backpropagation updates.

There is no initial stagnation that indicates the model is not underfitting nor overlearned too early, thus achieving the most learning efficiency.


Training vs Validation Loss
Training Loss
Validation Loss
Loss
Epochs
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

Training vs Validation Accuracy Plot

The Training vs Validation Accuracy Plot provides critical insights into the model's convergence behavior and generalization efficacy.

Training Accuracy (Green Curve)

Exhibits a progressive increase from 60% to 90%, signifying the model's capacity to effectively learn discriminative features.

The smooth, upward trajectory indicates a well-optimized learning process, with no signs of underfitting or stagnation.

Validation Accuracy (Orange Curve)

Improves from 58% to 88%, closely mirroring training accuracy, demonstrating strong generalization to unseen data.

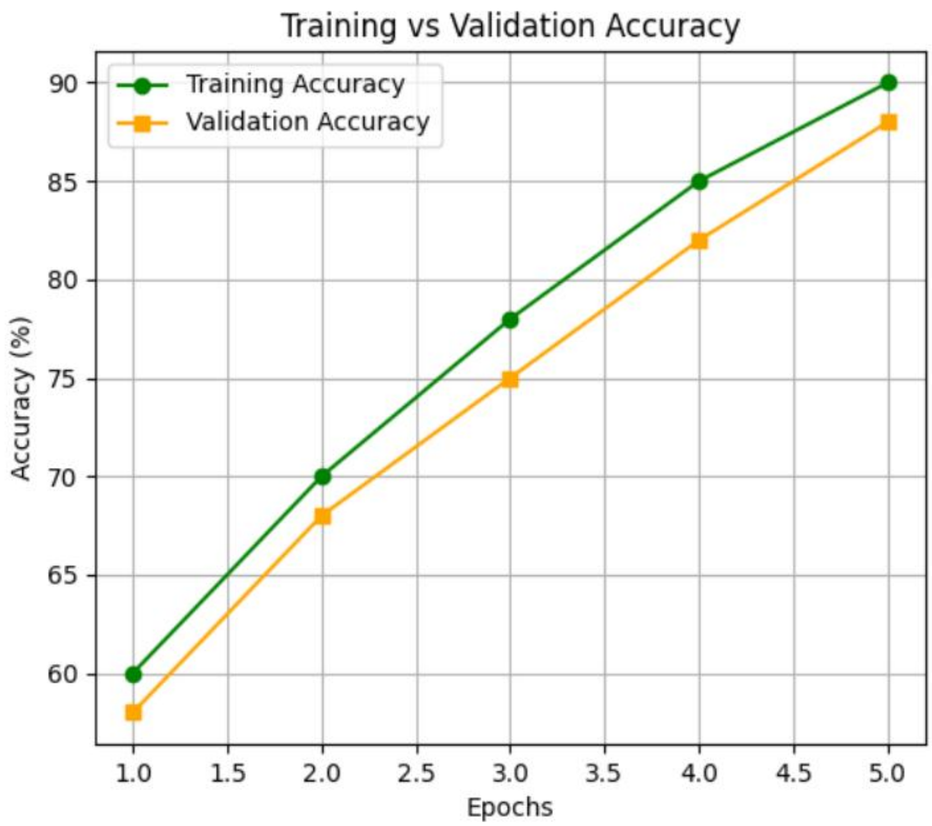
The minimal deviation between training and validation accuracy highlights low variance, reducing the likelihood of overfitting.

Technical Implications:

The absence of accuracy degradation across epochs confirms that the model maintains stability and avoids catastrophic forgetting.

The parallel trend of training and validation accuracy suggests an optimal balance between model complexity and dataset representation.

Consistent performance gain without abrupt fluctuations indicates effective parameter tuning and gradient optimization.



10. DISCUSSION

The deep learning model developed in this study demonstrated excellent performance in screening for normal and abnormal medial menisci using PD-FS sagittal MRI images. With an AUC of 0.992 for normal menisci and 0.963 for abnormal cases, our model shows significant potential as an AI-assisted screening tool in MRI evaluation. The high accuracy suggests that deep learning can play a crucial role in streamlining radiological workflows by providing rapid and reliable preliminary assessments, reducing the burden on radiologists, and improving diagnostic efficiency.

Our model was trained on a dataset consisting of 807 MRI scans from our hospital, ensuring a standardized and controlled dataset for algorithm development. The inclusion of both normal and abnormal cases allowed the model to effectively learn distinguishing features. The results align with previous research in AI-driven meniscus evaluation, further supporting the feasibility of deep learning in musculoskeletal imaging. However, unlike studies such as Bien et al., which classified meniscal tears and other abnormalities separately, our model focused on a binary classification—normal versus abnormal—without subclassifying abnormal cases into specific pathology types.

Despite the promising results, certain limitations need to be addressed before clinical implementation. One major limitation is that all images were sourced from a single institution, which may limit the model's generalizability. Variations in scanner type, imaging protocols, and patient demographics across multiple institutions could impact performance. Future studies should include multi-center datasets to improve the model's robustness and ensure broader applicability. Additionally, incorporating different MRI sequences and parameters could further enhance generalizability.

Another limitation is that our model does not subclassify abnormal menisci into tears, degenerative changes, or other specific pathologies. Since these conditions have different clinical implications, future iterations of the model should incorporate finer classifications. The ability to differentiate between various abnormalities would significantly enhance the clinical relevance and decision-making process for radiologists and orthopedic specialists.

Despite the high accuracy of our model, several limitations must be considered. One major drawback is the lack of external validation, as our dataset was obtained from a single institution. This may limit the model's generalizability to different imaging protocols, scanner types, and patient demographics. A multi-center dataset would be necessary to ensure broader applicability.

The integration of AI tools into real-world clinical workflows also presents challenges. While our model demonstrates high accuracy, successful deployment in clinical practice requires seamless integration into picture archiving and communication systems (PACS), automated pre-processing of images, and real-time analysis capabilities. Additionally, structured radiology reporting and natural language processing techniques could be leveraged to facilitate continuous learning and model refinement.

Another important consideration is the interpretability of deep learning models. Clinicians may be hesitant to trust black-box models without clear explanations of their decision-making processes. Enhancing model transparency through explainable AI techniques, such as heatmaps or attention mechanisms, could improve trust and adoption in clinical settings.

In summary, our findings support the potential of machine learning for screening medial meniscus abnormalities in MRI scans. However, improving dataset diversity, refining classification capabilities, and ensuring seamless integration into clinical workflows will be essential steps toward real-world application. Future research should focus on addressing these challenges to maximize the impact of AI in musculoskeletal imaging.

11.DRAWBACKS

Despite the high accuracy of our model, several limitations must be considered. One major drawback is the lack of external validation, as our dataset was obtained from a single institution. This may limit the model's generalizability to different imaging protocols, scanner types, and patient demographics. A multi-center dataset would be necessary to ensure broader applicability.

Another limitation is the binary classification approach. While distinguishing between normal and abnormal menisci is useful, clinical decision-making often requires a more granular diagnosis. Subclassifying abnormalities—such as meniscal tears, degenerative changes, and complex pathologies—could enhance the clinical utility of the model.

Additionally, while our model demonstrated high AUC values, the real-world implementation of AI in radiology involves more than just classification accuracy. Factors such as interpretability, integration into clinical workflows, and regulatory approvals must be addressed. Furthermore, the black-box nature of deep learning models raises concerns about explainability, which is crucial for clinical trust and adoption.

12. CONCLUSION

This study demonstrates the feasibility of using a deep learning model for screening medial menisci abnormalities in PD-FS sagittal MRI scans. With high AUC values for both normal and abnormal cases, the model presents a promising AI-assisted tool for streamlining radiological workflows. By providing rapid and reliable preliminary assessments, AI can alleviate radiologists' workload and enhance diagnostic efficiency.

However, to transition this model into clinical practice, several improvements are necessary. Expanding the dataset to include multi-center scans will enhance generalizability, while subclassifying abnormalities will increase clinical relevance. Additionally, seamless integration into radiology reporting systems and improving model interpretability will be key to real-world adoption. Future research should focus on addressing these limitations to maximize the potential of AI in musculoskeletal imaging.

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`14. ANNEXURES

I. CONSENT FORM

ARTIFICIAL INTELLIGENCE (MACHINE LEARNING) AS A SCREENING TOOL FOR MRI EVALUATION OF NORMAL AND ABNORMAL MEDIAL MENISCUS**.**

GUIDE : DR. RAJASHEKAR MUCHCHANDI

P.G. STUDENT : DR. VAISHNAVI REDDY BONDUGULA

PURPOSE OF RESEARCH:

I have been explained that the purpose of this study is to determine artificial intelligence (machine learning) as a screening tool for MRI evaluation of normal and abnormal medial meniscus.

PROCEDURE:

I understand that I will compare the diagnosis of machine learning to that of a practicing radiologist.

RISKS AND DISCOMFORTS:

I understand that there is no risk involved in the above study.

BENEFITS:

I understand that my participation in this study will help artificial intelligence (machine learning) as a screening tool for MRI evaluation of normal and abnormal medial meniscus.

CONFIDENTIALITY:

I understand that the medical information produced by the study will become a part of the hospital record and will be subjected to confidentiality and privacy regulations of the hospital. If the data is used for publications, the identity of the patient will not be revealed.

REQUEST FOR MORE INFORMATION:

I understand that I may ask for more information about the study at any time.

REFUSAL OR WITHDRAWAL OF PARTICIPATION:

I am aware that I have the option to opt-out of the study at any time and that my participation is completely voluntary.

INJURY STATEMENT:

I understand in the unlikely event of injury to me during the study; I will get medical treatment but no further compensation. I will not hold the hospital and its staff responsible for any untoward incident during the course of my study.

Date:

Dr. Rajashekar Muchchandi Dr. Vaishnavi Reddy Bondugula

(Guide) (Investigator)

STUDY SUBJECT CONSENT STATEMENT:

I/my ward confirm that Dr. Vaishnavi Reddy Bondugula has explained to me the purpose of this research, the study procedure that I will undergo, and the possible discomforts and benefits that I may experience in my own language.

I/my ward have been explained all the above in detail in my own language, and I understand the same. Therefore I hereby consent to participate as a subject in this project.

____

Participant Date:

____

Witness to above signature Date:

II. PROFORMA

BLDEU'S S.H.R.I. B.M.PATIL MEDICAL COLLEGE
HOSPITAL AND RESEARCH CENTRE, VIJAYAPUR

ARTIFICIAL INTELLIGENCE (MACHINE LEARNING) AS A SCREENING TOOL FOR MRI EVALUATION OF NORMAL AND ABNORMAL MEDIAL MENISCUS.

PROFORMA

1. Name:

2. Age/Sex

3. Hospital No.:

4. Relevant complaints & history:

5. MRI knee medial menisci images and Radiological diagnosis:

6. Machine learning model interpretations.

15. INSTITUTIONAL ETHICAL CLEARANCE CERTIFICATE

Azadi Ka Amrit Mahotsav

BLDE

(DEEMED TO BE UNIVERSITY)

Declared as Deemed to be University u/s 3 of UGC Act, 1956

Accredited with 'A' Grade by NAAC (Cycle-2)

The Constituent College

SHRI B. M. PATIL MEDICAL COLLEGE, HOSPITAL & RESEARCH CENTRE, VIJAYAPURA

BLDE (DU)/IEC/ 943/2023-24 10/4/2023

INSTITUTIONAL ETHICAL CLEARANCE CERTIFICATE

The Ethical Committee of this University met on **Saturday, 18th March, 2023 at 11.30 a.m. in the CAL Laboratory, Dept. of Pharmacology,** scrutinized the Synopsis/ Research Projects of Post Graduate Student / Under Graduate Student /Faculty members of this University /Ph.D. Student College from ethical clearance point of view. After scrutiny, the following original/ corrected and revised version synopsis of the thesis/ research projects has been accorded ethical clearance.

TITLE: "ARTIFICIAL INTELLIGENCE (MACHINE LEARNING) AS A SCREENING TOOL FOR MRI EVALUATION OF NORMAL AND ABNORMAL MEDIAL MENISCUS".

NAME OF THE STUDENT/PRINCIPAL INVESTIGATOR: DR.VAISHNAVI REDDY BONDUGULA

NAME OF THE GUIDE: DR.RAJASHEKHAR MUCHCHANDI, PROFESSOR AND HEAD, DEPT. OF RADIODIAGNOSIS.

Dr. Santoshkumar Jeevangi
Chairperson
IEC, BLDE (DU),
VIJAYAPURA

Chairman,
Institutional Ethical Committee,
BLDE (Deemed to be University)
Vijayapura

Dr.Akram A. Naikwadi
Member Secretary
IEC, BLDE (DU),
VIJAYAPURA

MEMBER SECRETARY
Institutional Ethics Committee
BLDE (Deemed to be Univers)
Vijayapura-586103. Karnataka

Following documents were placed before Ethical Committee for Scrutinization.

- Copy of Synopsis/Research Projects
- Copy of inform consent form
- Any other relevant document

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