Integrating Deep Learning with PACS Systems and Organizational Approaches for MRI Image Classification and Knee Injury Diagnosis

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***Abstract*— Recent advancements in artificial intelligence (AI) technologies have significantly impacted the enhancement of diagnostic processes, particularly in magnetic resonance imaging (MRI). This paper explores organizational strategies for optimizing diagnostic workflows through the integration of AI and Picture Archiving and Communication Systems (PACS). PACS, which manage and store medical images and facilitate communication between imaging data and analytical software, play a crucial role in effectively utilizing AI techniques for disease diagnosis.**

Deep learning models in MRI analysis, particularly for knee injuries such as anterior cruciate ligament tears and meniscus damage, demonstrate the high potential of these technologies to improve diagnostic accuracy and reduce errors. A key aspect of this study is the introduction of the PACS-AI platform, which serves as an interface between PACS systems and AI models. This platform enables automated, near real-time processing of medical images, providing immediate analytical results to users.

The paper also addresses challenges related to integrating AI into healthcare systems, including software compatibility issues and legal and ethical concerns, emphasizing the importance of developing necessary infrastructure for effective implementation of these technologies. Finally, the study examines future perspectives and research directions in the field of knee injury diagnosis using AI and PACS systems, offering recommendations for further improvements and development of these methods.

Keywords*— *AI in healthcare, PACS integration, MRI knee injury diagnosis, deep learning

I. Introduction

Magnetic Resonance Imaging (MRI) is the most widely used non-invasive imaging technique for diagnosing knee injuries. However, interpreting knee injuries based on MRI can be highly challenging, with the expertise of physicians playing a crucial role in image interpretation. Human-based image interpretation is prone to several issues, including subjectivity, distractions, fatigue, and diagnostic uncertainties, which often lead to inconsistent diagnoses and suboptimal management of knee injuries. Given these challenges, along with the exponential increase in clinical examinations, the idea of leveraging computers to enhance the complex task of interpreting medical imaging has recently gained acceptance in the scientific community. The proliferation of imaging data, algorithmic advancements, and recent technological progress in high-speed computing have driven a strong push toward the use of Artificial Intelligence (AI) algorithms in medical image analysis. Deep Learning (DL), a specific class of Machine Learning (ML) algorithms, has become a key driving force behind the current surge in AI (Siouras, Moustakidis et al. 2022). ML has had a large impact on the field of medicine, particularly in radiology (Jonske, Dederichs et al. 2022).

Picture Archiving and Communication System (PACS), which was originally designed as a tool for facilitating radiologists in interpreting images more efficiently, is evolving into a hospital-integrated system storing diagnostic imaging information that often reaches far beyond Radiology. In the last decades, PACS technology has supported the expansion of new tools for assisting diagnostic imaging. This evolution has been paralleled by workflow reorganisation in Radiology departments and has facilitated patient data management in hospitals (Faggioni, Neri et al. 2011).

PACS forms an integral part of medical imaging informatics, which concerns itself with the development and adaptation of techniques from medicine, engineering, computer science and other fields to create and manage medical data and knowledge and improve clinical care (Abbas and Singh 2019).

In recent years, machine learning models have been introduced to solve many problems in medical imaging, such as segmentation, classification, and disease prediction. Unfortunately, most of them are useless for the physician due that they are not available tools that are part of their workflow. At present, PACS are the standard platforms used in clinical environments to store and transmit electronic images and the reading reports. Therefore, the integration of the automatic analysis tools with these systems is required to allow validation by physicians and the use in clinical and medical research (Osorno-Castillo, Fonnegra et al. 2020).

In light of recent advancements in deep learning algorithms and medical imaging management systems, the integration of these technologies presents a unique opportunity to enhance the accuracy and efficiency of knee injury diagnosis. This paper explores the application of deep learning in MRI-based knee injury classification, focusing on the critical role that PACS systems play in facilitating this process. Additionally, it examines the organizational strategies necessary for successfully implementing AI-driven diagnostic tools within clinical environments, addressing both the challenges and opportunities that arise from the adoption of such technologies in modern healthcare settings.

II. Integration of PACS and Deep Learning

A. Functionality of PACS Systems

Since the emergence of a Picture Archiving and Communication System (PACS) in the early 1980s, we have witnessed revolutionary changes in radiology practice. Early years mostly dealt with the definition of large-scale PACS, establishment of Digital Imaging and Communications in Medicine (DICOM) and other standards, the development of some early key PACS-related technologies, and PACS implementation strategies. Concepts such as enterprise PACS, integrating the health care enterprise workflow profiles, and EMR (electronic medical records) with image distribution were developed later (Mansoori, Erhard et al. 2012).

The term PACS applies to networks of digital image modalities, image workstations and mass image stores connected among each other by image data communication structures and controlled by appropriate image and data management. Predominantly, PACS are intended for application in the medical imaging domain, particularly in hospitals (Meyer-Ebrecht 1994).

Medical imaging is a critical component in rendering patient care. The system that provides the acceptance, transfer, display, storage, and digital processing of medical images is known as a PACS and is nearly ubiquitous in healthcare environments(Shields 2010).

In recent years, there have been major changes in imaging, storage, and network requirements. Despite the high initial costs of PACS, rapid technological advancements and open communication standards have led to significant cost reductions. Modern PACS systems allow for two-dimensional reading of cross-sectional images, three-dimensional reconstructions, and even four-dimensional imaging. Additionally, the use of advanced online post-processing tools has increased diagnostic accuracy and improved collaboration between radiologists and other specialists. It is anticipated that advanced PACS will be able to handle newer data types, such as metabolic data, which will be used for the next generation of diagnostic procedures (Shields 2010).

A lack of IT knowledge has been identified as one of the main challenges in the implementation of PACS systems, as PACS software training requires a basic understanding of IT. Resistance to change has also been reported as a challenge. Users without IT experience show the most resistance. Additionally, the lack of change management and leadership during these processes creates challenges in the implementation and training phases. Finally, other challenges, such as hospitals' inaccurate estimation of image storage needs, have also been highlighted (Abbas and Singh 2019).

With the growing number of digital medical imaging records, the need for an automatic procedure to retrieve only data of interest is of increasing importance. A Picture Archiving and Communication System (PACS) provides effective storage and retrieval based on TAGs but does not allow us for query by example (Gravina, Marrone et al. 2021).

In summary, PACS has transformed radiology by revolutionizing how medical images are stored, shared, and interpreted. With advancements in imaging, storage, and network technologies, modern PACS systems have enhanced diagnostic accuracy and enabled more seamless collaboration among healthcare professionals. However, challenges such as the need for IT expertise and resistance to change remain key obstacles to successful implementation. As the volume of imaging data continues to grow, integrating PACS with advanced tools like deep learning is increasingly critical. This integration promises to further enhance diagnostic capabilities and optimize workflows, leading to improved patient outcomes in the next generation of medical imaging.

B. Applying Deep Learning to MRI Classification

The use of machine learning (ML) has been rapidly increasing in the medical imaging field, including computer-aided diagnosis (CAD), radiomics, and medical image analysis. Recently, a branch of ML called deep learning has emerged in the field of computer vision and has become very popular in many areas. This trend began with an event in late 2012, when a deep learning method based on convolutional neural networks (CNN) achieved a decisive victory in the prestigious international computer vision competition, ImageNet Classification. Since then, researchers in almost all fields, including medical imaging, have actively entered the rapidly growing field of deep learning (Suzuki 2017). Primary ML methods are categorized into supervised learning, unsupervised learning and reinforcement learning (RL) (Kim, Yun et al. 2019).

Due to its superior soft-tissue contrast, absence of ionizing radiation, and flexibility of contrast mechanisms, MRI is a common imaging method to evaluate joints. Specifically, it is used for the detection and assessment of acute and chronic internal derangement injuries of the knee. MRI is useful in the characterization of injuries to the cruciate ligaments, collateral ligaments, menisci, and extensor mechanism, as well as abnormalities of the cartilage and bone marrow. One major challenge of MRI is that data acquisition is slow in comparison to other modalities (Johnson, Lin et al. 2023).

Supervised ML systems (Figure 1) operate in two phases: the learning phase (training) and the testing one. In a traditional ML pipeline, a feature extraction/selection stage (also referred to as feature engineering) is first implemented to extract or identify the most informative features [16]. These features can be extracted from the input images, employing various algorithms including grey-level co-occurrence matrix (GLCM), first- and second-order statistics, and shape/edge features, among others [30]. Next, an ML model is fit to the extracted features and the optimal model parameters are obtained. During the testing phase, the trained model is shown previously unseen samples (represented as images or features extracted from images), which are then classified. As opposed to traditional programming, where the rules are manually crafted by a programmer, a supervised ML algorithm automatically formulates rules from the data (Siouras, Moustakidis et al. 2022).

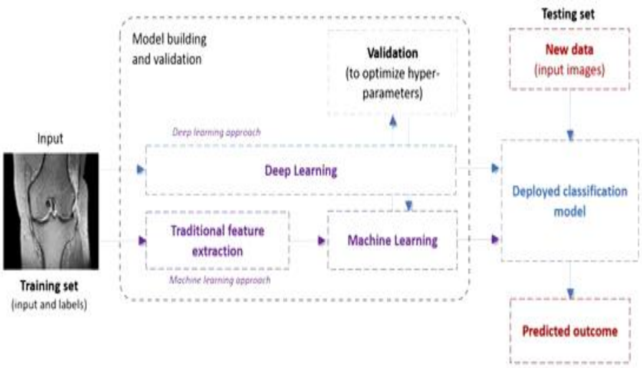

Figure. 1. This figure illustrates the training and testing phases of a supervised ML system, including feature engineering to extract key features

In DL, the algorithm itself extracts the most informative features for the task at hand. The mainstream DL architecture for computer vision applications is the convolutional neural network (CNN) (Liu 2019).
A CNN typically consists of multiple building blocks (layers such as convolutional, pooling, and fully connected) that automatically extract increasingly abstract spatial hierarchies of features. As shown in Figure 2, the CNN structure automatically extracts features, and training is performed via the backpropagation algorithm The CNN training is carried out via a backpropagation algorithm. The huge popularity of CNNs is attributed to certain characteristics they possess, such as weight sharing and spatial invariance (Liu 2019).

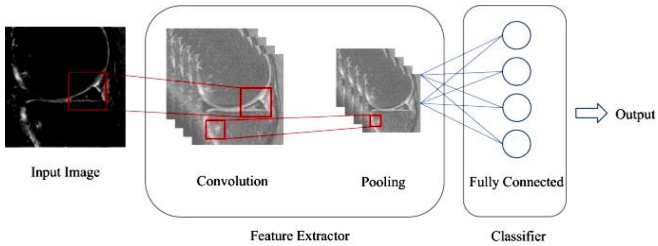

Figure. 2 .Shows the structure of a CNN, where layers automatically extract features, with training done via backpropagation

MRI data of the knee, complemented by massive amounts of associated, multi-dimensional data such as omics and electronic health records, are only expected to grow. To fully exploit the full potential of this wealth of data, new paradigms should arise involving processes and workflows suitable for multi-institutional collaboration. Moreover, addressing the need for trustworthy detection systems of knee injuries, a medical diagnosis algorithm should meet a number of requirements (e.g., transparency, interpretability, explainability, and ease of use) in order to gain trust from clinicians. AI explainability and lightweight deep learning are key enablers for the wide use of such systems in the everyday clinical practice. Exploiting the intersection and merits of traditional ML and DL methods, AI analytics are expected to revolutionize knee medical informatics, enabling informed and accurate diagnoses needed by precision medicine (Siouras, Moustakidis et al. 2022)
Artificial intelligence (AI) has made impressive strides, especially in medicine. Machine learning, a key part of AI, helps systems recognize patterns in data without needing specific instructions. Deep learning, a type of machine learning, uses neural networks that mimic the human brain to understand complex information. Convolutional neural networks (CNNs) are particularly good at analyzing images, automatically identifying important features. Although CNNs are powerful, they can be difficult to interpret, so tools are used to make their decision-making more transparent.

III. Organizational Strategies for Enhancing Diagnosis

A. *Implementing AI in Healthcare Settings*

Artificial intelligence (AI) aims to replicate human cognitive functions. This technology is bringing significant changes to the healthcare sector, fueled by greater access to healthcare data and rapid advancements in analytical techniques. AI can be applied to various types of healthcare data (structured and unstructured). Popular AI techniques include machine learning methods for structured data, such as classical support vector machines and neural networks, modern deep learning, as well as natural language processing for unstructured data (Jiang, Jiang et al. 2017).
AI is increasingly becoming a crucial tool in image analysis, aiding radiologists in the early diagnosis of various diseases and minimizing diagnostic errors (Al Kuwaiti, Nazer et al. 2023).
Artificial intelligence (AI) is transforming healthcare by mimicking human cognitive functions and utilizing vast amounts of data. A key component of AI in healthcare is Artificial Neural Networks (ANNs), which are multilayered structures that replicate brain activity and have demonstrated superior performance in cardiology over traditional models like logistic regression. Machine Learning (ML) encompasses a variety of algorithms designed to learn from data and identify patterns. Among these, supervised learning methods, which include logistic regression, Bayesian networks, and ANNs, use labeled data to predict clinical outcomes and survival rates. On the other hand, unsupervised learning techniques analyze data without predefined labels, utilizing methods such as clustering and principal component analysis to improve disease prediction accuracy(Jiang, Jiang et al. 2017).
Deep Learning, a specialized subset of ML, involves neural networks with multiple hidden layers to process complex data and has shown significant promise in cardiac imaging. This approach enhances tasks such as endocardium tracking and left ventricle segmentation. Convolutional Neural Networks (CNNs), a specific type of deep learning network, are particularly effective in image analysis and have proven useful in medical imaging, such as calculating coronary artery calcium from CT scans. Overall, these AI technologies contribute to better diagnostic accuracy, more reliable disease prediction, and improved decision-making in various medical fields, including cardiology, oncology, and neurology (Jiang, Jiang et al. 2017).
However, the integration of AI in healthcare faces numerous challenges. Variability among healthcare systems, reliance on proprietary software, and rising cybersecurity threats pose significant issues. Additionally, AI models must be evaluated through prospective studies and in environments

that closely mimic clinical settings, a process that requires specialized software and is difficult to achieve. The use of AI techniques in healthcare also raises substantial legal and ethical concerns, including patient privacy protection, prevention of bias, and monitoring of device safety and efficacy for regulatory compliance. The aim of PACS-AI is to facilitate the evaluation and validation of AI models by integrating them with existing medical imaging databases, potentially overcoming many current barriers to AI adoption (Theriault-Lauzier, Cobin et al. 2024).
The PACS-AI platform is designed to be vendor-agnostic, serving as an interface between existing clinical PACS systems, where medical images and reports are stored, and AI models. Its primary goal is to enable the automated and near real-time application of AI models to clinical images at the point of care. The platform provides a web application interface that allows clinicians to search for imaging studies within the hospital PACS and select a compatible AI model for processing the associated images. The application backend retrieves the relevant images, prepares the data, and performs AI inference. The results are then displayed to the user through the web interface (Theriault-Lauzier, Cobin et al. 2024).

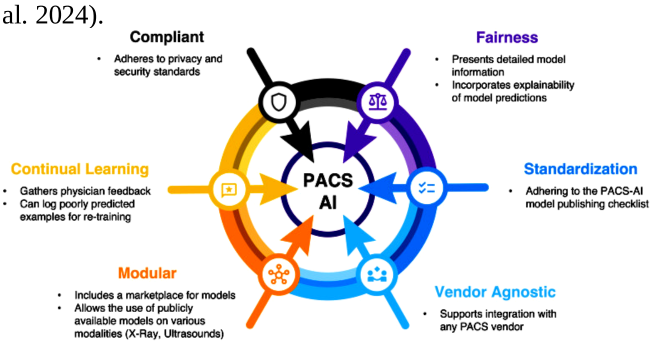

Figure 3Features of the PACS-AI platform. AI, artificial intelligence; PACS, Picture Archives Communication System.

For successful implementation of AI in PACS (Picture Archiving and Communication Systems), it is crucial to ensure seamless integration between PACS systems and AI models. This involves ensuring full compatibility between PACS software and AI models, creating user-friendly interfaces for searching and selecting models, and providing the necessary infrastructure for near real-time image processing and analysis. Additionally, attention must be given to legal and ethical considerations to ensure patient privacy and regulatory compliance are maintained.

B. *Optimizing Knee Injury Diagnosis with AI*

Deep learning-based analysis of joint MRI exams is an emerging field of artificial intelligence, which offers many exciting possibilities for musculoskeletal radiology. Current DL algorithms for MRI diagnoses of internal derangement focus on the detection of ACL tears, meniscus tears, and rotator cuff tears, as well as rotator cuff muscle segmentation (Fritz and Fritz 2022).
In a study, it was shown that radiology departments have been leading deep learning development for injury detection on knee MRIs. Although studies inconsistently described DL model development details, all reported high model performance, indicating great promise for DL in knee MRI analysis (Santomartino, Kung et al. 2024).
The results of an article demonstrate that machine learning algorithms have the potential to serve as valuable assistants to radiologists in evaluating MRIs, providing an efficient means of diagnosing knee pathologies. With further improvements in the algorithms, incorporation of larger datasets, and refinement of the model, machine learning-based approaches can enhance the diagnostic accuracy and efficiency in the field of knee imaging, ultimately leading to improved patient care and outcomes (Mangone, Diko et al. 2023).
In summary, deep learning has shown great potential in enhancing the accuracy and efficiency of knee injury diagnosis through MRI analysis. Despite some inconsistencies in the development and description of models, the overall performance of AI-driven approaches remains highly promising. With further advancements, including larger datasets and model refinement, deep learning can become an invaluable tool for radiologists, significantly improving diagnostic capabilities and patient outcomes in musculoskeletal imaging.

IV. Perspectives and Areas for Further Research

A. *Trends in AI and Imaging Technologies*

Artificial Intelligence (AI) broadly refers to the theory and development of computer systems capable of performing tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation. These advanced computer systems have the capacity to perform tasks generally associated with human intelligence. Machine learning and deep learning algorithms are subsets of AI, and their applications in medical imaging practice are becoming increasingly common. AI is recognized for offering unique advantages in medical imaging practice, such as reducing diagnostic errors, alleviating workplace stress, and providing clinical decision support to radiologists and radiographers.

A joint statement from the International Society of Radiographers and Radiological Technologists (ISRRT) and the European Federation of Radiographer Societies (EFRS) has highlighted that AI systems can optimize imaging workflows, aid in dose reduction, increase research efficiency, and consistently deliver high-quality planning processes. Consequently, AI is generally accepted as a vital tool in practice, with medical imaging professionals at the forefront of this advancement (Botwe, Akudjedu et al. 2021).
The integration of artificial intelligence (AI) into medical imaging is progressing rapidly, with advancements reflecting a significant evolution from the early days of AI research. AI, encompassing machine learning (ML) and deep learning (DL), is increasingly applied to various imaging modalities and therapeutic areas.
AI has shown substantial promise in enhancing the analysis of medical images, significantly reducing diagnostic errors and providing decision support. The introduction of AI into medical imaging began in earnest in the 1970s, with foundational work that laid the groundwork for future applications. The term "AI in Medicine" was established in

1991 during the first conference of the Artificial Intelligence in Medicine Europe (AIME) organization, marking a formal recognition of AI's role in healthcare.

Recent advancements highlight a trend toward more sophisticated applications of AI in medical imaging. Notably, deep learning has emerged as a powerful tool due to its ability to tackle complex visual information problems with remarkable accuracy. CNNs and other deep learning models are now commonly used for tasks such as image segmentation, object recognition, and lesion classification.

Despite the progress, there are still challenges to overcome. Radiologists are slow to adopt AI, with a significant portion reporting limited familiarity with its applications. Nonetheless, AI is recognized for its potential to optimize imaging workflows, reduce radiation doses, and improve overall diagnostic efficiency.

In summary, the trends in AI and imaging technologies reveal a growing integration of advanced AI techniques, particularly deep learning, in medical imaging. These developments promise to enhance diagnostic accuracy and efficiency while presenting new opportunities and challenges for the field (Olveres, González et al. 2021).

Recent advancements in artificial intelligence (AI) have brought significant changes to medical imaging. Initially, the focus was on applying machine learning (ML) and deep learning (DL) techniques from computer vision to medical applications, such as organ segmentation and dose prediction. As the field progresses, there is a growing emphasis on integrating domain-specific knowledge into AI models to enhance their performance and interpretability. This includes incorporating medical data like electronic health records and using expert knowledge to guide AI predictions. Additionally, active learning methods are being explored to iteratively improve models by querying for new, valuable data.

The quality of data remains a critical factor, with challenges such as gender imbalance and racial bias potentially impacting model outcomes. Addressing these issues requires improved data collection and curation practices, as well as the adoption of federated learning approaches to maintain data privacy. Overall, a multidisciplinary effort involving computer science, IT, and medical experts is essential for successfully integrating AI into clinical workflows and developing robust, interpretable solutions for medical imaging (Barragán-Montero, Javaid et al. 2021).

B. *Exploring New Research Avenues in Knee Injury Diagnosis*

Arthroscopy is widely considered the gold standard for diagnosing the pathology of knee abnormalities (Patel, Hartigan et al. 2018). However, this inspection method cannot detect some knee abnormalities located outside the joint cavity (e.g., bone contusion, infrapatellar fat pad injury, and patellar retinaculum injury) (Diederichs, Issever et al. 2010) and carries the risk of additional trauma and serious complications (e.g., joint infection and deep vein thrombosis) (Qiu, Xie et al. 2024). Magnetic resonance imaging (MRI) is a non-invasive method for accurate evaluation of knee pathology and provides results comparable to those of arthroscopy (Nacey, Geeslin et al. 2017). In addition to conventional T1- and T2-weighted (T1W and T2W) imaging sequences, knee MRI requires proton density-weighted (PDW) imaging sequence because of its high signal-to-noise ratio and spatial resolution to accurately detect abnormalities. However, knee MRI interpretation is very time-consuming and labor-intensive. Some subtle lesions of the knee joint can easily be overlooked by radiologists with insufficient work experience. Therefore, automatic methods have a huge clinical demand for accurate diagnosis of knee abnormalities (Qiu, Xie et al. 2024).

In recent years, several automated approaches, including classical methods and DL models, have been proposed to assist in knee abnormality diagnosis from MRI (Qiu, Xie et al. 2024) with the corresponding knee MRI dataset collected to facilitate related research (Štajduhar, Mamula et al. 2017, Bien, Rajpurkar et al. 2018)However, the existing studies mainly focused on a few common abnormalities, such as tears in the meniscal and anterior cruciate ligaments, which limits the model when adapting to more complex real-life cases (Qiu, Xie et al. 2024).

V. Conclusion

This paper underscores the significant impact of artificial intelligence (AI) on improving diagnostic accuracy and efficiency, particularly through integration with PACS. AI technologies, including machine learning and deep learning, are transforming the analysis of MRI images for knee injuries by enabling more precise and timely diagnoses.

The use of AI within PACS frameworks facilitates seamless, automated analysis of medical images, enhancing both diagnostic accuracy and workflow efficiency. While progress has been notable, challenges such as software compatibility and data privacy remain. Addressing these issues requires ongoing development and collaboration among healthcare professionals and technology experts.

Future research should focus on optimizing AI models and expanding their applications to cover a wider range of conditions. By continuing to advance these technologies and integrating them effectively with PACS, we can improve diagnostic practices and patient outcomes.

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