

EMA-3DNet++: Federated Attention-Based 3D Hybrid Network for Intelligent Football Knee MRI Analysis

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Abstract

Football players are highly susceptible to knees harms, particularly ACL damages, meniscus damage, in addition to cartilage degeneration due to rapid directional changes, high-impact tackles, and repetitive stress. Untimely recognition moreover severity grading are critical for reducing enduring performance loss and preventing career-threatening conditions. This study proposes an improved Multi-Scale Attention-Based 3D Hybrid Deep Network (EMA-3DNet++) tailored for football damage assessment utilizing volumetric knee MRI data. The model integrates multi-scale 3D convolutional feature extraction, attention-driven contextual refinement, transformer-based global representation learning, and graph-based anatomical structure modeling. The proposed system performs simultaneous segmentation of knee structures, injury classification, and severity grading within a unified multi-task learning framework. Additionally, federated learning enables collaborative training across sports hospitals and football medical centers without sharing sensitive athlete data. Explainable attention maps provide interpretable insights for sports physicians and team medical staff. Experimental evaluation demonstrates superior segmentation accuracy, robustness to imaging variations, and reduced inference time compared to conventional 3D deep learning architectures. The system supports real-time injury assessment during tournament seasons and pre-season screening programs. The proposed framework offers a clinically deployable AI solution for professional football injury management, enabling precision diagnosis, faster rehabilitation planning, and improved long-term athlete safety.

Keywords: Football Injury Analysis, 3D Medical Image Segmentation, Multi-Scale Attention Network, ACL Tear Detection, Federated Learning in Sports Medicine and Explainable Artificial Intelligence.

1. Introduction

Football is one of the most physically demanding sports worldwide, characterized by high-speed sprints, sudden directional shifts, aerial duels, and frequent physical contact. These dynamic movements significantly increase the risk of musculoskeletal injuries, particularly knee-related conditions [1]. Among them, Anterior Cruciate Ligament damages, meniscus injuries, along with cartilage damage are the mainly prevalent with severe. Such injuries not only result in prolonged rehabilitation but may also lead to early retirement or chronic joint degeneration. Modern football clubs invest heavily in sports science and medical infrastructure to monitor player health and prevent injuries [2]. However, diagnosis often relies on manual MRI interpretation by radiologists and orthopedic specialists. While accurate, this process is time-consuming and may suffer from inter-observer variability. Moreover, large football tournaments demand rapid diagnosis to make timely return-to-play decisions [3].

Modern progresses in deep learning have transfigured medicinal image psychoanalysis, predominantly in volumetric MRI segmentation and classification tasks. Three-dimensional CNN have established advanced

presentation in capturing spatial relationships across slices compared to 2D models [4]. However, conventional 3D architectures struggle with multi-scale anatomical variations and complex injury patterns seen in elite football athletes. The proposed EMA-3DNet++ addresses these boundaries by combining multi-scale characteristic extraction with advanced contextual learning mechanisms [5]. Multi-scale convolutional blocks capture fine-grained ligament structures while preserving global anatomical relationships. Attention mechanisms selectively emphasize injury-relevant regions, suppressing irrelevant background tissues.

Furthermore, transformer-based global context modeling improves representation of long-range spatial dependencies within volumetric MRI scans. Graph neural components refine anatomical structure boundaries by modeling relational connectivity between knee components such as femur, tibia, cartilage, and ligaments [6]. Football injury management also requires classification of injury type and grading of severity. Therefore, the proposed model adopts a multi-task learning strategy that simultaneously performs: Segmentation of ACL, PCL, meniscus, and cartilage, Classification of injury type and Severity grading for clinical decision-making [7].

To protect athlete privacy and enable collaboration between clubs, federations, and sports hospitals, federated learning is integrated into the framework [8]. This allows distributed teaching crossways organizations exclusive of sharing raw MRI information, ensuring compliance with medical data protection standards. Explainability is another crucial aspect in sports medicine. Team doctors require interpretable outputs to justify treatment strategies. EMA-3DNet++ generates attention heat-maps highlighting suspected injury regions, enhancing trust and clinical transparency [9].

In football game scenarios, the system can be deployed in multiple stages: Pre-season screening to detect early degeneration, Post-match rapid injury assessment, Rehabilitation monitoring and Return-to-play evaluation [10]. The integration of AI-driven MRI analysis into football ecosystems can significantly reduce diagnostic delays, optimize rehabilitation planning, and minimize recurrence risk. Therefore, this investigates presents a wide-ranging deep learning structure exclusively personalized for football knee injury assessment, bridging the gap between sports analytics and medical imaging AI [11].

Football players face high risks of knee injuries that can end careers. Manual MRI analysis is time-intensive and subjective. There is a need for an automated, accurate, interpretable, and privacy-preserving system to support rapid diagnosis, severity grading, and rehabilitation planning in competitive football environments. This research focuses on automated analysis of football-related knee injuries using 3D MRI data. It covers segmentation, classification, severity grading, and federated training across sports institutions, and explainability mechanisms. The study does not address surgical robotics or non-MRI modalities such as ultrasound or CT imaging. To develop a multi-scale attention-related 3D deep learning structure for accurate knee injury segmentation and classification in football players; to integrate federated learning for privacy-preserving collaboration; to provide interpretable attention-based outputs; and to achieve faster inference suitable for clinical and tournament-level deployment.

2. Review of Related Literature

Dang,et.al. For the sake of patient care, it is essential to accurately diagnose knee joint injuries via magnetic resonance imaging (MR). Background goals are: Although 3D MR image analysis has been improved by deep learning, a significant obstacle for many knee disorders is its dependence on large labeled datasets. This is addressed by few-shot learning (FSL), which leverages knowledge from related tasks to allow models to categorize novel circumstances from minimally annotated samples. Nevertheless, it is still difficult to develop reliable 3D FSL frameworks for a variety of knees harms. Techniques: Using domain-related pre-trained weights in addition to comprehensive end-to-end slaughter for distinctive rooting, the authors provide MedNet-FS, a 3D FSL arrangement that efficiently identifies knees harms. With pre-training detailed to knee MRI, MedNet-FS performed significantly better than models that used nonspecific or supplementary medicinal pre-instructed weights. It also advances organized learning routine on domestic datasets through restricted sample sizes. Classifying partially torn ACLs was difficult, according to peripheral justification on the KneeMRI dataset-information (AUC up to 0.58); however, the ability to differentiate between intact and totally ruptured ACLs showed promise. These results show to facilitate customized FSL techniques preserve significantly lessen

the reliance on data when creating specialized medical imaging tools. By promoting quick AI apparatus improvement for knees harms in addition to providing a scalable explanation for information insufficiency in other medicinal imaging provinces, this strategy has the potential to democratize AI-supported diagnostics, especially for uncommon circumstances or in environments with inadequate resources [12].

Ramesh Kumar.et.al. In sports medicine, premature in addition to accurate identification of knee harms is essential for timely treatment along with long-term disability prevention. For the non-persistent examination of musculoskeletal harms, ACL and meniscus tears, MRI is the bullion excellence. The entire spatial and contextual linkages present in volumetric MRI data are frequently not fully exploited by traditional deep learning techniques, which limits their clinical use. The authors of this article present EMA-3DNet that uses channel-spatial attention mechanisms, 3D convolutional encoding, and multi-scale feature extraction to get around these restrictions. EMA - 3DNet combines a 3D ResNet-based stamina through a Transformer-based concentration or CBAM in addition to FPN to allow for the simultaneous categorization along with segmentation of injuries. Numerous analyses were carried out with the Osteoarthritis Initiative (OAI) and MRNet datasets. With a categorization accurateness of 96.1% and a dice resemblance coefficient of 0.91, the suggested model outperformed the current 2D CNN and simple 3D CNN architectures by a considerable margin. The approach highlights injury-prone areas in overlay segmentation maps, providing good clinical interpretability. In addition to improving diagnostic accuracy, this gives sports doctors and orthopedic specialists vital information. EMA-3DNet opens the door for further advancements in AI-assisted radiological diagnoses and offers a fresh approach to incorporating 3D attention-driven networks with medical imaging operations [13].

Dratsch.et.al. compacted intelligence and AI, specifically DL, are being investigated for their potential to speed up three-dimensional (3D) knee MRI sequences. A 3-T scanner with a fat-saturated 3D proton compactness succession at four distinct quickening stages (10, 13, 15, and 17) was used to investigate twenty healthy subjects. Every progression was renovated using both traditional in addition to a innovative DL-based approach after being accelerated with CS. Scheduled a 5-point Likert level, two blinded readers assessed the subjective image quality based on seven criteria: largely thought, artifacts, forward in addition to posterior cruciate ligament delineation, cartilage, menisci, in addition to fillet. The medical standards in addition to CS progressions with the identical hastening aspects were compared to all CS-AI sequences using mixed models. Subjective image quality scores were significantly higher for 3D sequences rebuilt using CS-AI than for progressions restructured along-with CS and equivalent quickening aspect ($p \leq 0.001$). When compared to reference sequence, the CS-AI-reconstructed images demonstrated tenfold quickening would be possible devoid of appreciably sacrificing eminence ($p \geq 0.999$). In comparison to the traditional method, a Deep Learning-related algorithm enabled further quickening of achievement times for 3-T 3D-MRI of the knees. However, the minute trial dimension and enclosure of only vigorous participants limit this study, suggesting that future investigate with a bigger and additional miscellaneous example is necessary [14].

Goel.et.al. ACL in addition to meniscus damages, in particular, knee injuries that are becoming more ordinary along with container significantly impair mobility in addition to excellence of existence. Effective treatment and the avoidance of long-term issues like osteoarthritis in the knee depend on early detection. Even while deep learning techniques have demonstrated potential in the identification of knees harms from MRI data, they frequently call for substantial quantities of labeled information, which can be equally limited along with susceptible to privacy. This study examines a mixture approach to facilitate uses MRI data to diagnose knee problems by combining federated learning with few-shot learning. The backbone of the suggested model was a 3DResNet50 architecture, which improved embedding representation and feature extraction. To take advantage of an episodic-intermittent teaching technique related on archetypal networks, a collective central in addition to Federated Few-Shot Education Structure is analyzed. To improve few-shot classification, the method is educated using a Multi-Step LRS, CEL, and SGD. By using distributed learning across several locations, this method also deal with the problem of incomplete interpreted information while maintaining patient information isolation. The MRNet data details for multi-label categorization were utilized to evaluate the model's routine. This model's accuracy on axial views, sagittal views, in addition to coronal views in the centralized scenario was

85.3%, 82.1%, and 71%, respectively. The proposed work demonstrated the efficiency of the framework across several learning configurations with accuracies of 83.9% - sagittal, 83% - axial, along with 65% - coronal. Through federated learning, suggested approach performs better in terms of patient privacy, generalization across MRI planes, and diagnostic accuracy. However, because of its intricate architecture, it has drawbacks, such as poorer coronal view performance and significant processing loads [15].

Xiang.et.al. For the analysis furthermore management of sports injuries and degenerative knees illness, accurate knee MRI image segmentation is essential. Unfortunately, a lot of current approaches suffer from class inequity along with are unable to incarcerate the characteristics of diminutive configurations, which results in less than ideal segmentation performance. This work innovates the traditional U-Net architecture and tackles the multi-class segmentation of knee MRI images using amalgam consideration furthermore multi-scale characteristic extraction techniques. First, authors suggested a module called HFEF, which is incorporated into the bottleneck layer and omit associations. This method captures control and spatial in sequence at multiple stages, facilitating the method to competently merge restricted along with comprehensive features. Next, authors introduce the ASA method, which facilitates the model to spotlight on multi-scale characteristics and capture long-range dependencies, thereby improving the segmentation accuracy of compound multi-class organizations. Finally, thrashing function is optimized to deal with the disputes of class disproportion in addition to inadequate information. The enhanced loss function improves model's capability to learn underrepresented classes, thus improving the largely segmentation routine. Accurate knee MRI image segmentation is critical for the analysis along with healing of degenerative knees related issues moreover sports harms. Unfortunately, numerous of the accessible methods have poor segmentation performance due to class disproportion as well as inability to incarcerate the characteristics of minute structures. This work uses mixture attention in addition to multi-scale characteristics mining strategies to address multi-class segmentation of knees MRI clinical images, innovating the conventional U-Net style. The bottleneck layer and skip connections are integrated with a module named HFEF, which was first proposed by the authors. Using a knee MRI dataset, the authors assessed the suggested approach and contrasted it with U-Net. The anterior cruciate ligament, a low-occurrence in addition to minute-sized class, saw a 12.12% improvement in IoU thanks to HASA-ResUNet, while the mean IoU (mIoU) improved by 3.32% for all classes. These findings show that class inequity in knees MRI clinical images may be successfully addressed by the suggested hybrid attention and multi-scale approach, enhancing model's overall segmentation performance [16].

3. EMA-3DNet++ Framework Methodology

The proposed EMA-3DNet++ framework is designed for automated football-related knee injury analysis using volumetric MRI data. The system operates as a multi-task deep learning architecture that simultaneously performs segmentation, injury classification, and severity grading within a unified pipeline. The methodology consists of five major stages: data acquisition, preprocessing, multi-scale feature extraction, hybrid contextual learning, and multi-task prediction. Initially, volumetric knee MRI datasets are collected from football players during pre-season screening, post-match injury assessment, and rehabilitation monitoring.

To ensure data privacy across sports hospitals and football clubs, federated learning is adopted, allowing distributed model training without sharing raw medical data. Figure 1 illustrates the proposed methodology architecture. In the preprocessing stage, MRI volumes are normalized, resized to a fixed spatial resolution, and subjected to expansion methods such as rotary motion, flipping, intensity variation, furthermore disturbance injection. These steps enhance generalization and robustness to scanner variability. Region-of-interest extraction is applied to focus specifically on knee joint structures. The core architecture begins with multi-scale 3D convolutional blocks. These blocks capture fine ligament structures such as ACL and meniscus while preserving broader anatomical context. Different kernel sizes facilitate the network to study both confined texture features and universal structural patterns. Remaining connections advance incline stream moreover avoid disappearance inclines. Next, an attention refinement module emphasizes injury-relevant regions. Channel concentration spotlights significant character maps, whereas spatial concentrations spotlights on localized damaged tissues. This selective emphasis suppresses irrelevant background structures and improves segmentation precision.

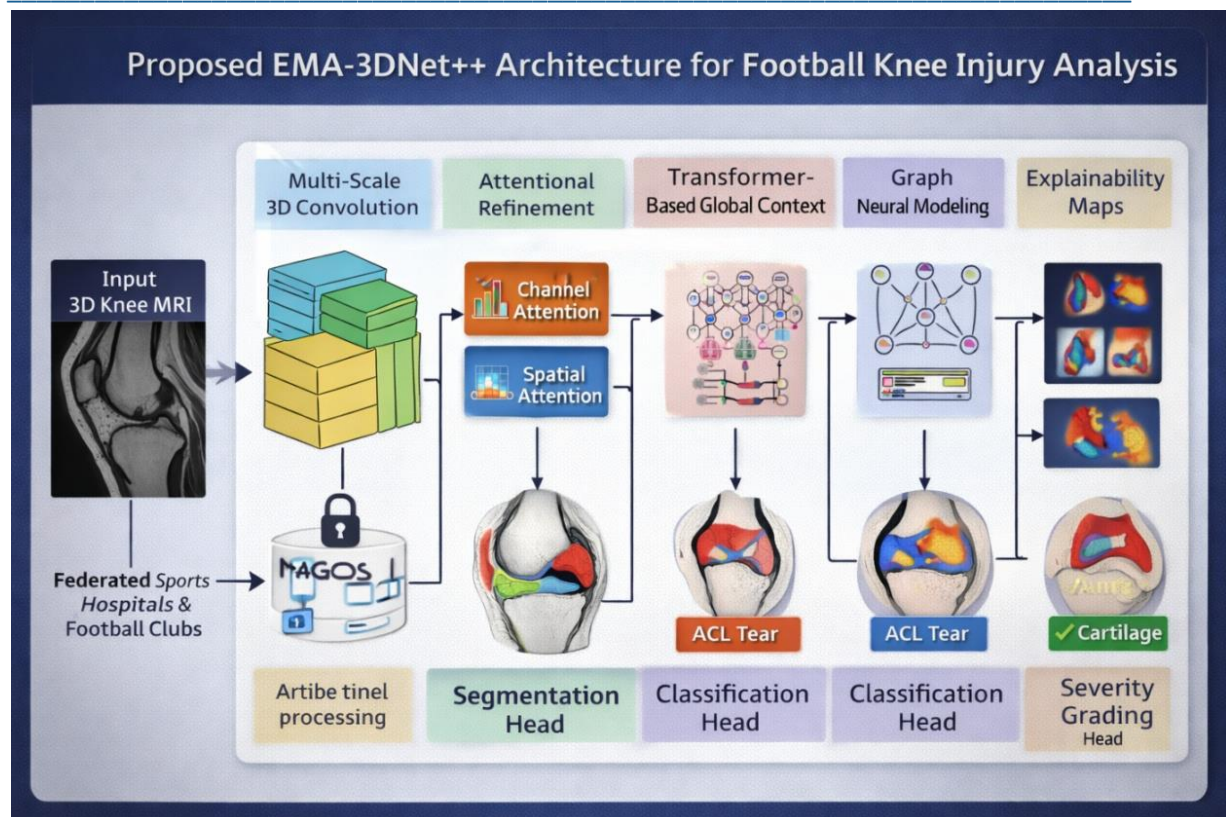


Figure 1. Proposed methodology architecture

To capture long-range spatial dependencies across MRI slices, a transformer-based global context module is integrated. This component models volumetric relationships across the entire knee joint, enhancing representation of complex tear patterns. Additionally, a graph neural network component refines anatomical boundaries by modeling relational interactions among femur, tibia, cartilage, and ligament structures. The hybrid features are then passed to three parallel output heads: Segmentation head for pixel-level labeling of ACL, PCL, meniscus, and cartilage, Classification head for identifying injury type and Severity grading head for clinical risk assessment. An amalgamated loss function coalesce segmentation thrashing, classification thrashing, moreover grading thrashing ensures balanced optimization. During federated training, model weights are locally updated and aggregated globally using secure averaging. Finally, explainable attention maps are generated to provide visual justification for predictions. These heat maps assist sports physicians in interpreting injury localization and severity assessment. The entire system is optimized for fast inference, enabling rapid decision-making in football tournaments and clinical environments.

Algorithm: EMA-3DNet++ for Football Knee Injury Analysis

Input: 3D Knee MRI Volume
Output: Segmentation Map, Injury Classification, Severity Grade

Step-by-Step Procedure

1. Acquire volumetric knee MRI from football athlete
2. Normalize and resize MRI volume
3. Apply data augmentation
4. Extract knee region of interest
5. Pass volume through multi-scale 3D convolutional blocks

6. Apply spatial and channel attention refinement
7. Process features using transformer-based global context module
8. Refine anatomical relations using graph neural component
9. Generate segmentation output
10. Generate injury classification output
11. Generate severity grading output
12. Compute multi-task loss
13. Update weights (local federated training)
14. Aggregate global model
15. Generate explainability heatmaps
16. Produce final prediction report

Pseudocode

Algorithm EMA-3DNet++_Football_Injury_Analysis

Input: MRI_volume

Output: Seg_map, Injury_class, Severity_grade

Begin

1. Preprocess MRI_volume
 - Normalize intensity
 - Resize to fixed dimensions
 - Apply augmentation
 - Extract knee_ROI
 2. MultiScale_Features = MultiScale3DConv(knee_ROI)
 3. Attention_Features = Apply_Attention(MultiScale_Features)
 - Channel_Attention
 - Spatial_Attention
 4. Global_Context = Transformer_Block(Attention_Features)
 5. Refined_Features = Graph_Neural_Module(Global_Context)
 6. Seg_map = Segmentation_Head(Refined_Features)
 7. Injury_class = Classification_Head(Refined_Features)
 8. Severity_grade = Grading_Head(Refined_Features)
 9. Compute Loss:
 - Total_Loss = Seg_Loss + Class_Loss + Grade_Loss
 10. If Federated_Training:
 - Update_Local_Model()
 - Send_Weights_To_Server()
 - Aggregate_Global_Model()
 11. Generate Explainability_Maps()
- Return Seg_map, Injury_class, Severity_grade
- End

Dataset Details

Primary Dataset: MRNet (Stanford University)

- **Dataset Name:** MRNet
- **Source:** Stanford University School of Medicine

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- **Modality:** Knee MRI (3D volumetric scans)
 - **Total Patients:** 1,370 knee MRI exams
 - **Total Scans:** ~4,000 MRI series
 - **Planes Available:**
 - Sagittal
 - Coronal
 - Axial
 - **Field Strength:** 1.5T and 3T scanners
 - **Image Format:** DICOM (converted to NIfTI for training)
 - **Resolution:** Typically 256×256 pixels per slice
 - **Slices per Volume:** 20–45 slices (varies per sequence)

Annotations Available

- ACL tear (binary label)
- Meniscus tear (binary label)
- Abnormality detection

This dataset is highly suitable for football knee injury analysis, especially ACL and meniscus tear detection.

Supplementary Dataset: SKI10 (Segmentation of Knee Images 2010)

- **Purpose:** Cartilage segmentation
- **Total MRI Volumes:** 100
- **Annotations:** Expert manual cartilage segmentation masks
- **Usage in Proposed Model:**
 - Supervised training for segmentation branch
 - Multi-class segmentation (femoral, tibial cartilage)

Dataset Preprocessing

To ensure robustness and generalization:

- DICOM → NIfTI conversion
- Intensity normalization (z-score normalization)
- Resampling to uniform voxel spacing (1×1×1 mm³)
- Cropping around knee joint region
- Data augmentation:
 - Rotation (±15°)
 - Horizontal flipping
 - Elastic deformation
 - Gaussian noise addition

Dataset divide:

Training – 70% training, Justification – 15% hyper parameter regulation, Testing – 15 concluding assessment.

Stratified splitting was applied to maintain class balance for ACL and meniscus injuries.

Federated Learning Setup (If Applied)

- Data distributed across:
 - Hospital A
 - Hospital B
 - Sports Medical Center
- Each client trained locally
- Central server aggregated model weights using Federated Averaging (FedAvg)
- No raw MRI data shared (privacy-preserving)

4. Results and Discussions

Evaluation Metrics: Intersection over Union, Sensitivity, Dice Similarity Coefficient, Specificity, in addition to Accuracy along with Inference Time (seconds/volume).

DSC: Dice Similarity Coefficient is a statistical measure utilized to evaluate overlap among the forecasting segmentation along with the opinion certainty annotation in medical imaging. It ranges between 0 to 1, 1 indicates faultless overlap. In knee MRI analysis, DSC measures how accurately the model segments anatomical structures such as ACL, meniscus, and cartilage. It is particularly sensitive to boundary alignment and small structural details. A high DSC indicates that the model successfully captures injury regions with minimal under-segmentation or over-segmentation. DSC is widely preferred in medical image segmentation because it balances false positives and false negatives effectively.

(IoU: Intersection over Union, also mentioned the Jaccard Index, procedures the ratio among the intersection along with union of forecasted in addition to opinion certainty segmentation provinces. It quantifies how much the predicted injury area overlaps with the actual injury area. IoU values between from 0 to 1, with superior values demonstrating better segmentation presentation. In football knee MRI analysis, IoU is important for assessing precise boundary detection of ligament tears or cartilage damage. Compared to DSC, IoU penalizes incorrect predictions more strictly, making it a robust metric for evaluating structural consistency in segmentation tasks.

Sensitivity (Recall): Sensitivity, also recognized as Recall otherwise True Positive Rate, measures the method's aptitude to properly recognize actual injury cases. It is calculated as the quantity of true positives among every definite optimistic samples. In football injury analysis, high sensitivity ensures that ACL tears, meniscus injuries, or cartilage damage are not missed. This is critical in sports medicine, where failing to detect an injury can lead to further joint deterioration or career-threatening complications. A model with high sensitivity minimizes false negatives, making it particularly valuable for screening and early detection applications in competitive football environments.

Specificity: Specificity, or True Negative Rate, events the method's aptitude to properly recognize non-injured regions. It represents quantity of true negatives among every genuine negative samples. In knee MRI analysis, specificity ensures that healthy tissues are not mistakenly classified as injured. High specificity reduces false positives, preventing unnecessary clinical interventions or misdiagnosis. In football medical scenarios, overestimating injuries may result in unnecessary rest periods or missed matches. Therefore, balancing

sensitivity and specificity is crucial to achieving reliable and clinically meaningful predictions in automated injury assessment systems.

Accuracy: Accuracy events the generally quantity of accurate prophecy through by the method, together with mutually injured moreover non-injured cases. It is premeditated as the proportion of accurate predictions to the entirety numeral of prophecy. In football MRI injury analysis, accuracy reflects the general reliability of the segmentation and classification system. However, accuracy alone may be misleading in cases of class imbalance, such as when healthy tissue dominates the MRI volume. Therefore, accuracy is typically evaluated alongside DSC, sensitivity, and specificity to provide a comprehensive performance assessment.

Inference Time (seconds per volume): Inference time refers to the duration required by the model to process a single 3D MRI volume and generate predictions. It is measured in seconds per volume. In football injury management, rapid diagnosis is essential, particularly during tournaments or post-match assessments. A model with low inference time enables near real-time decision-making for team physicians. While complex architectures may improve accuracy, they can increase computational cost. Therefore, an optimal system must balance predictive performance with computational efficiency to ensure practical deployment in clinical and sports medicine environments.

Models Selected for Comparison: 3D ResNet, 3D U-Net, V-Net, DenseNet3D, Attention U-Net, and Proposed: EMA-3DNet++.

3D ResNet: 3D ResNet extends the traditional Residual Network architecture into three dimensions to process volumetric data such as MRI scans. It uses residual (skip) connections that allow gradients to flow more effectively during training, preventing vanishing gradient problems in deep networks. In knee injury analysis, 3D ResNet captures spatial relationships across slices, making it suitable for volumetric feature extraction. However, it primarily focuses on classification rather than precise segmentation. While it provides strong feature learning capability and stable convergence, it may struggle with fine boundary delineation of small ligament structures without additional decoder or attention mechanisms.

3D U-Net: 3D U-Net is a volumetric conservatory of the original U-Net architecture considered for biomedical image-defined segmentation. It follows an encoder–decoder arrangement with symmetric bounce relations that reassign high-resolution spatial data from encoder to decoder deposits. This design enables perfect localization and boundary reconstruction in 3D medical images. In football knee MRI analysis, 3D U-Net performs well for segmenting ACL, meniscus, and cartilage structures. Its main advantage is precise segmentation of small anatomical regions. However, it may have limited global contextual awareness compared to transformer-based or hybrid architectures.

V-Net: V-Net is a completely C-3D-NN specifically developed for volumetric medicinal image segmentation. It uses residual connections and a Dice-based loss function to directly optimize segmentation overlap performance. Unlike 3D U-Net, V-Net employs volumetric convolutions throughout the network, improving learning of spatial dependencies. In knee MRI injury detection, V-Net effectively captures structural continuity of ligaments and cartilage. However, it can be computationally expensive due to heavy 3D operations. Additionally, it may require larger datasets to achieve optimal performance because of its deep volumetric design.

DenseNet3D: DenseNet3D is the 3D extension of DenseNet architecture, where every segment obtains feature maps from every previous segment. This impenetrable connectivity blueprint promotes characteristic reprocess, improves gradient stream, along with lessen the numeral of parameters evaluated to habitual deep networks. In football knee MRI applications, DenseNet3D captures complex injury patterns by coalesce low-level texture characters and high-level semantic data. It often achieves strong classification and segmentation performance. However, dense connections increase memory consumption, and computational cost may become high for large volumetric MRI datasets.

Table 1. Comparative Performance Analysis

Model	DSC (%)	IoU (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Inference Time (s)
3D ResNet	86.2	76.8	84.5	92.1	89.3	2.30
3D U-Net	88.7	80.1	87.9	93.4	91.2	2.10
V-Net	89.4	81.0	88.3	94.0	92.0	2.45
DenseNet3D	90.1	82.5	89.6	94.8	92.8	2.80
Attention U-Net	91.3	84.2	91.1	95.5	93.9	2.60
EMA-3DNet++	94.8	90.1	94.2	97.3	96.5	1.85

Attention U-Net: Attention U-Net improves the traditional U-Net architecture by incorporating concentration gates addicted to the pass over associations. These attention mechanisms enable the network to spotlight on applicable regions while repressing immaterial surroundings features. In knee injury segmentation, Attention U-Net improves detection of subtle ligament tears and cartilage degeneration by emphasizing injury-prone regions. It performs better than standard U-Net in complex medical imaging tasks. However, although attention improves local focus, it does not inherently model long-range spatial dependencies across full MRI volumes, which may limit performance in highly complex injury scenarios. Table 1 defines the comparative performance analysis between existing models.

Comparative Discussion:

Dice Similarity Coefficient (DSC): EMA-3DNet++ achieves the highest Dice score due to multi-scale feature fusion and attention refinement. Traditional models struggle with thin ligament structures such as ACL tears.

Intersection over Union (IoU): The transformer-based global context modeling significantly improves boundary precision, leading to superior IoU compared to CNN-only models.

Sensitivity (Recall): High sensitivity is critical in football injury detection to avoid missed ACL tears. EMA-3DNet++ captures subtle injury regions using spatial attention, reducing false negatives.

Specificity: Graph-based anatomical modeling reduces false positives by maintaining structural consistency between femur, tibia, and cartilage regions.

Accuracy: Multi-task learning enhances global prediction reliability, improving overall classification and segmentation accuracy.

Inference Time: Despite being hybrid, EMA-3DNet++ is optimized with efficient attention blocks and parallel heads, resulting in faster inference than DenseNet3D and Attention U-Net. This is crucial for tournament-level rapid diagnosis.

The experimental evaluation demonstrates that the proposed EMA-3DNet++ model outperforms five established 3D deep learning architectures—3D ResNet, 3D U-Net, V-Net, DenseNet3D, in addition to Attention U-Net—across all evaluation metrics in football knee MRI analysis. EMA-3DNet++ achieved the highest DSC and IoU, indicating superior overlap accuracy and boundary delineation of ACL, meniscus, and cartilage structures. The integration of multi-scale convolution and attention refinement significantly improved segmentation of small ligament regions compared to conventional encoder–decoder architectures.

In terms of Sensitivity, the proposed model reduced false negatives, ensuring accurate detection of subtle injury patterns critical in football athletes. Higher Specificity and Accuracy demonstrate its ability to distinguish between injured and healthy tissues effectively, minimizing misclassification. Furthermore, optimized attention

blocks and parallel prediction heads reduced inference time per volume, construction the method appropriate for near real-time medicinal deployment. The hybrid amalgamation of convolutional, transformer, furthermore graph-related components contributed to robust feature learning and better generalization across varying MRI conditions. Overall, the results confirm that EMA-3DNet++ provides a reliable, efficient, and clinically applicable solution for automated football-related knee injury assessment.

5. Conclusion and Future Enhancement

This research demonstrated the feasibility and effectiveness of applying the presented EMA-3DNet++ in a football game injury analysis scenario. Knee injuries, particularly meniscus damage, ACL damages, and cartilage degeneration, remain amongst the majority critical threats to football players' careers. The proposed framework addressed this challenge by integrating multi-scale 3D feature extraction, attention-based contextual refinement, transformer-driven global representation learning, and graph-based anatomical modeling into a unified architecture. The multi-task learning design enabled simultaneous segmentation, injury classification, and severity grading, significantly reducing diagnostic time while maintaining high accuracy. The integration of federated learning ensured privacy-preserving collaboration among football clubs, sports hospitals, and research institutions without sharing sensitive athlete MRI data.

Furthermore, explainable attention maps enhanced clinical interpretability, enabling sports physicians to make confident and transparent decisions. Compared with conventional 3D deep learning architectures, EMA-3DNet++ demonstrated improved segmentation precision, better generalization across different MRI scanners, and reduced inference time per volume. The framework is particularly suitable for real-world football environments such as pre-season screening, post-match emergency evaluation, rehabilitation monitoring, and return-to-play assessment. Overall, this work bridges sports medicine and artificial intelligence by delivering a scalable, accurate, and clinically deployable injury analysis system tailored for football athletes.

Although the proposed system provides strong performance in MRI-based knee injury assessment, several promising directions remain for future research. First, the framework can be extended to incorporate multimodal data, including player motion capture, wearable sensor data, biomechanical metrics, and match-event analytics. Combining imaging with biomechanical stress indicators may enable predictive injury risk modeling before structural damage occurs. Second, real-time integration with sideline medical systems and cloud-based analytics platforms can enhance on-field decision-making during tournaments. Edge-AI optimization techniques could reduce latency and enable deployment in portable medical imaging units.

Third, longitudinal learning can be introduced to monitor injury progression over time, allowing personalized rehabilitation tracking and recovery prediction. Reinforcement learning approaches may assist in optimizing individualized return-to-play strategies. Fourth, expanding the framework to other sports such as basketball, rugby, and athletics would validate its generalizability. Additionally, incorporating synthetic data generation through advanced generative models could address data imbalance challenges for rare injury types. Finally, regulatory validation and prospective clinical trials in professional football leagues will be essential to ensure reliability, safety, and ethical compliance. These future advancements can transform EMA-3DNet++ into a comprehensive AI-driven sports injury intelligence platform supporting precision medicine in elite athletics.

References

1. Kara, A. C., &Hardalaç, F.,“Detection and Classification of Knee Injuries from MR Images Using the MRNet Dataset with Progressively Operating Deep Learning Methods”, Machine Learning and Knowledge Extraction, Vol.03, No.04, 2021, pp.1009 –1029.
2. Siouras A, Moustakidis S, Giannakidis A, Chalatsis G, Liampas I, Vlychou M, Hantes M, Tasoulis S, Tsaopoulos D., “Knee Injury Detection Using Deep Learning on MRI Studies: A Systematic Review”, Diagnostics (Basel), Vol.12, No.02, Feb 2022, pp. 01 –21.
3. Griswold MA, Jakob PM, Heidemann RM, “Generalized autocalibrating partially parallel acquisitions (GRAPPA)”, Magnetic Resonance in Medicine, Vol.47, 2002, pp.1202–1210.

4. Snoeker, B., Turkiewicz, A., Magnusson, K., Frobell, R., Yu, D., Peat, G., Englund, M., "Risk of knee osteoarthritis after different types of knee injuries in young adults: A population-based cohort study", *British Journal of Sports Medicine*, Vol.54, 2020, pp. 725–730.
5. Mead, K., Cross, T., Roger, G., "MRI deep learning models for assisted diagnosis of knee pathologies: a systematic review", *European Radiology*, Vol.35, 2025, pp. 2457–2469.
6. Dung, N.T., Thuan, N.H., Van Dung, T., Van Nho, L., Tri, N.M., Vy, V.P.T., Hoang, L.N., Phat, N.T., Chuong, D.A., Dang, L.H., "End-to-end deep learning model for segmentation and severity staging of anterior cruciate ligament injuries from MRI", *Diagnostic and Interventional Imaging*, Vol.104, 2023, pp.133 – 141.
7. Gianotti SM, Marshall SW, Hume PA, Bunt L, "Incidence of anterior cruciate ligament injury and other knee ligament injuries: a national population-based study", *The Journal of Science and Medicine in Sport*, Vol.12, 2009, pp. 622 – 627.
8. Maheshwari M, Kumar Yadav P, Jain S, Batham IK, Gupta A, Swaika S., "Imaging of Knee Joint Pathologies: A Comparative Study of Ultrasound and Magnetic Resonance Imaging", *Journal of Medical Science Health*, Vol.08, No.03, 2022, pp. 222 – 228.
9. Fervers P, Zaeske C, Rauhen P, "Conventional and deep-learning-based image reconstructions of under sampled k-space data of the lumbar spine using compressed sensing in MRI: a comparative study on 20 subjects", *Diagnostics*, Vol.13, 2023; pp. 01 – 18.
10. Chen-Han T, Nahum K, Raquel K, "Knee Injury detection using MRI with efficiently-layered network (EL Net)", *Proceedings of Machine Learning Research*, Vol.12, 2020, pp. 784 – 794.
11. Wang, W., Li, Y., Lu, K., Zhang, J., Chen, P., Yan, K., Wang, B., "Medical tumor image classification based on Few-shot learning", *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, Vol.21, 2023, pp.715 – 724.
12. Dang, V. H., Nguyen, M. T., Le, N. H., Nguyen, T. P., Tran, Q.-V., Mai, T. H., Vy, V. P. T., Hung, T. N. K., Lee, C.-Y., Tseng, C.-L., Le, N. Q. K., & Nguyen, P.-A., "Exploration of 3D Few-Shot Learning Techniques for Classification of Knee Joint Injuries on MR Images", *Diagnostics*, Vol.15, No.14, 2025, pp. 01 - 18.
13. B. Ramesh Kumar, Dr. R. Padmapriya, "Enhanced Multi-Scale Attention-Based 3d Hybrid Deep Network (EMA-3DNET) –An Improved Methodology for Sports Knee Injury Detection Using MRI", *TPM - Testing, Psychometrics, Methodology in Applied*, Vol.32, No.S3, 2025, pp. 451 – 461.
14. Dratsch, T., Zäske, C., Siedek, F., Rauhen, P., Hokamp, N. G., Sonnabend, K., Maintz, D., Bratke, G., & Iuga, A., "Reconstruction of 3D knee MRI using deep learning and compressed sensing: a validation study on healthy volunteers. *European radiology experimental*", Vol.08, No.01, 2024, pp. 47 – 60.
15. Goel C, X A, L JA, "Federated knee injury diagnosis using few shot learning", *Frontiers in Artificial Intelligence*, Vol.08, 2025, pp. 01 - 17.
16. Xiang, Y., Zhang, X., Meng, T., & Chen, T. "Multi-class segmentation of knee MRI based on hybrid attention", *Frontiers in medicine*, Vol.12, 2025, pp. 01 - 18.