A Systematic Review of Deep Learning Methods for ACL Tear Detection and Grading

Laya Hamehkhani | Dr. Mahdi Hossieni

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ACL Injuries - Clinical Burden

The Clinical Challenge

- **Epidemiology & Impact**
  - **200,000+ ACL injuries** annually in the United States alone
  - Peak incidence: **16-39** years (active population)
  - **Female** athletes: **2-8× higher risk** than **males** in comparable sports

- **Diagnostic Complexity**
  - Accuracy varies by reader experience: **86-94% (expert)** vs. **50-75% (general radiologist)**
  - Partial tears: Most challenging to diagnose, highest inter-reader variability

- **Clinical Significance**
  - Delays in diagnosis → Progressive joint instability → **Secondary injuries**
  - **Misclassification** of partial vs. complete tears → **Inappropriate treatment decisions**
  - Long-term: **50%** develop osteoarthritis within **10-20 years post-injury**

Current Diagnostic Workflow & Bottlenecks

MRI-Based Diagnosis: Standard of Care

- MRI Protocol for ACL Assessment
  - **Primary sequences:** Proton density (PD), T2-weighted, Fat-suppressed
  - **Key imaging planes:** Sagittal (primary), Coronal, Axial
  - **Target structures:** ACL morphology, signal intensity, fiber continuity
  - **Indirect signs**: Bone bruising, PCL angle, anterior tibial translation
- **Current Workflow Limitations**

Challenge	Impact	Quantification
Reading time	Radiologist workload	10-20 min per knee MRI
Manual segmentation	Research/surgical planning bottleneck	1-2 hours per case
Inter-reader variability	Inconsistent reporting	Cohen's κ: 0.42-0.65 (moderate)
Subtle tear detection	Missed partial tears	15-30% miss rate for grade I-II
Multi-abnormality assessment	Cognitive overload	12+ potential pathologies to evaluate
Experience dependency	Quality variation across centers	20-40% accuracy gap

Why Deep Learning for ACL Diagnosis?

The Convergence of Technology and Clinical Need

- **Unique Advantages of DL in Musculoskeletal Imaging**
  - 1. **Pattern Recognition at Scale**
    - Learns hierarchical features from raw pixel data
    - Captures subtle patterns invisible to human eye
    - Processes multi-planar, multi-sequence data simultaneously
  - 2. **Consistency & Reproducibility**
    - Eliminates inter-reader variability
    - Provides objective, quantifiable metrics
  - 3. **Computational Efficiency**
    - Real-time processing: <1 second vs. minutes
    - Scalable to high-volume clinical settings
    - Enables comprehensive multi-structure analysis
- **From Research to Clinical Reality**
  - **FDA clearances** emerging for orthopedic AI tools (2019-present)
  - Multiple **commercial platforms** in development
  - Integration with **PACS/radiology** workflows advancing

MRI Fundamentals Quick Reference

MRI Fundamentals Quick Reference

- **MRI Sequences Mentioned in This Review**

Sequence	Appearance	Primary Use in ACL Imaging
T1-weighted	Fat: bright, Fluid: dark	Anatomical detail, bone marrow
T2-weighted	Fluid: bright, Fat: intermediate	Edema, effusion detection
PD (Proton Density)	Balanced signal	ACL fiber visualization (primary)
Fat-Suppressed (FS)	Fat: dark, Fluid: very bright	Tear/edema sensitivity ↑

- **Image Planes**
  - **Sagittal:** Side-to-side slices (divides left/right)
  - **Coronal:** Front-to-back slices (divides front/back)
  - **Axial:** Top-to-bottom slices (divides superior/inferior)
- **ACL MRI Apearance**
  - **Normal:** Hypointense (dark), continuous fibers, 5-8mm thick, taut band
  - **Torn:** Discontinuous, hyperintense signal, irregular/absent fibers, wavy/lax

  Note: Deep learning models learn these patterns directly from data

Category 1: Segmentation-Based Approaches

Precise Anatomical Structure Identification

- **Focus:** Automated pixel-level segmentation of knee anatomical structures including **ACL**, PCL, cartilage, meniscus, and surrounding tissues

- **Key Applications:**
    - **Pre-surgical planning** and **3D visualization**
    - Reducing manual segmentation time (from 1-2 hours to <1 second)
    - **Multi-tissue analysis for comprehensive knee assessment**
    - Handling class imbalance challenges (small structures like ACL)

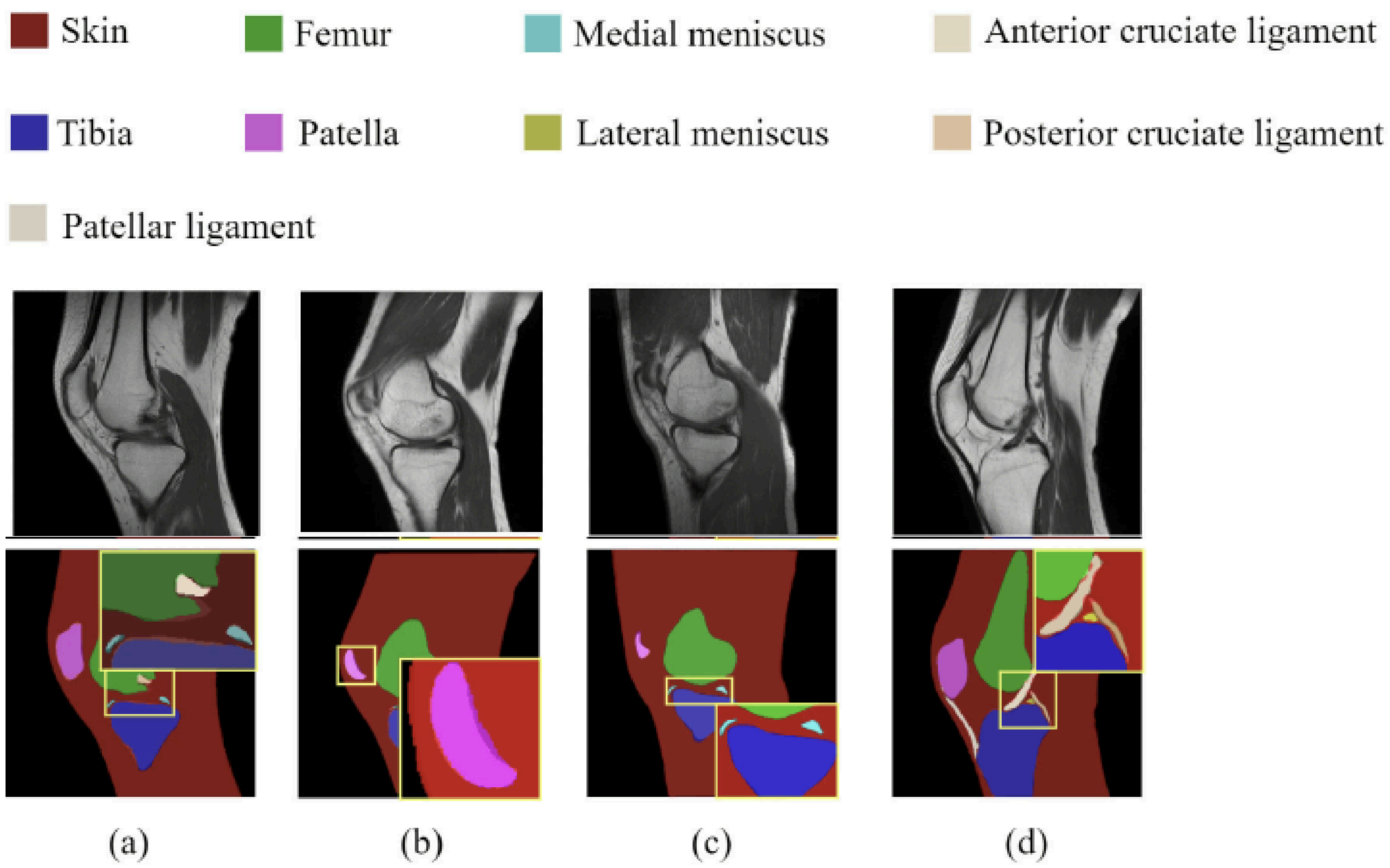
- **Clinical Value:**
    - Enables **precise measurement** of anatomical structures
    - Supports **holographic 3D modeling for surgical planning**
    - Foundation for downstream classification tasks

HASA-ResUNet

Hybrid Attention & Residual U-Net for Multi-Class Segmentation

- **Architecture:**
  - Novel U-shaped encoder-decoder network
  - Residual blocks replace standard convolutional layers
  - Mitigate vanishing gradient problem

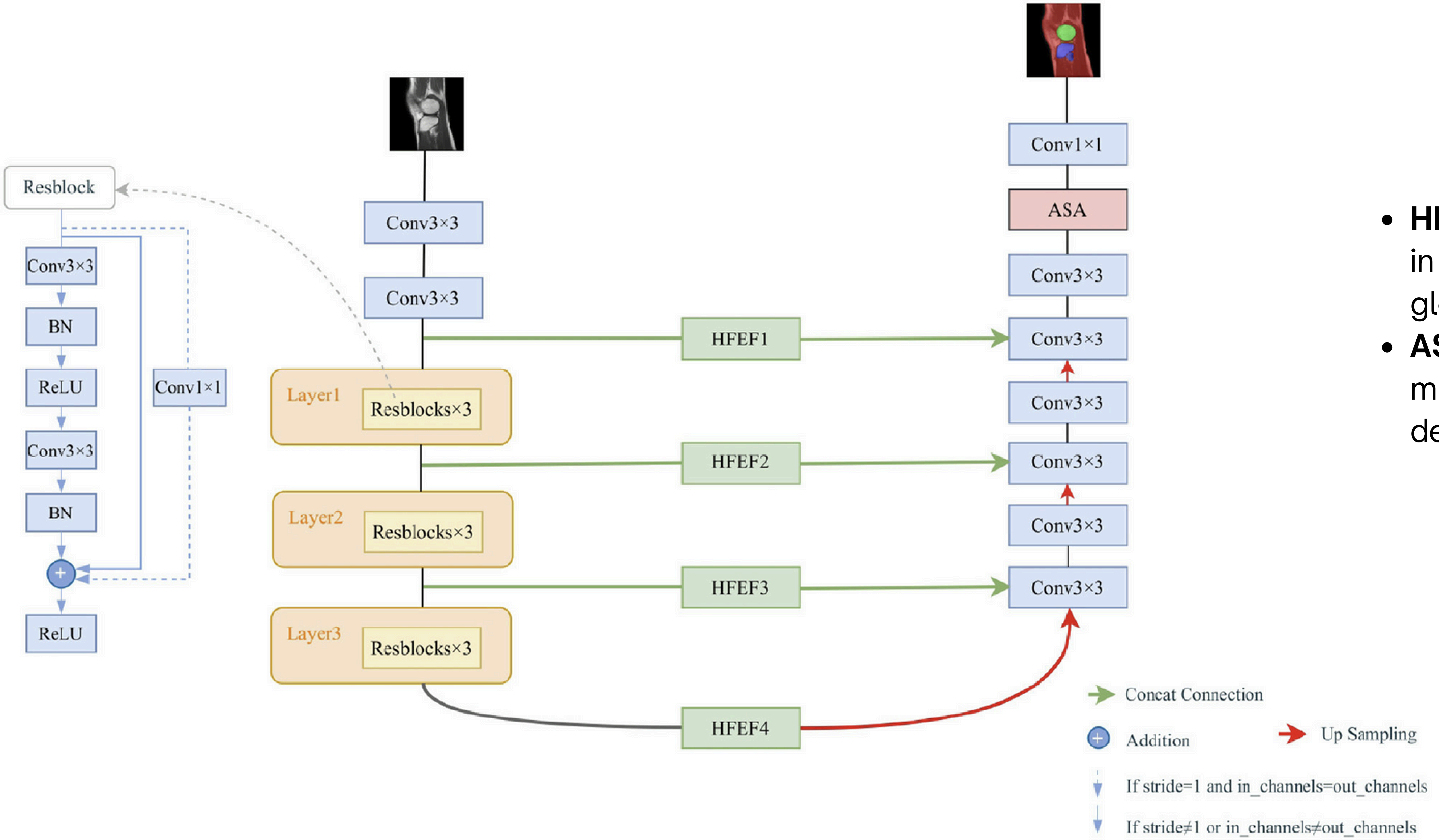
- **Key Innovations:**
  - Addresses **pixel imbalance** (small structures like **ACL**)
  - Handles **blurred boundaries** effectively
  - Manages **shape diversity** in multi-class knee MRI segmentation



Visual segmentation results of the knee joint generated by the models.

HASA-ResUNet

Hybrid Attention & Residual U-Net for Multi-Class Segmentation



The structure of HASA-ResUNet

- **HFEF Module:** Hierarchical feature fusion in skip connections → combines local + global features
- **ASA Module:** Atrous squeeze attention → multi-scale focus + long-range dependencies

3D DenseVNet

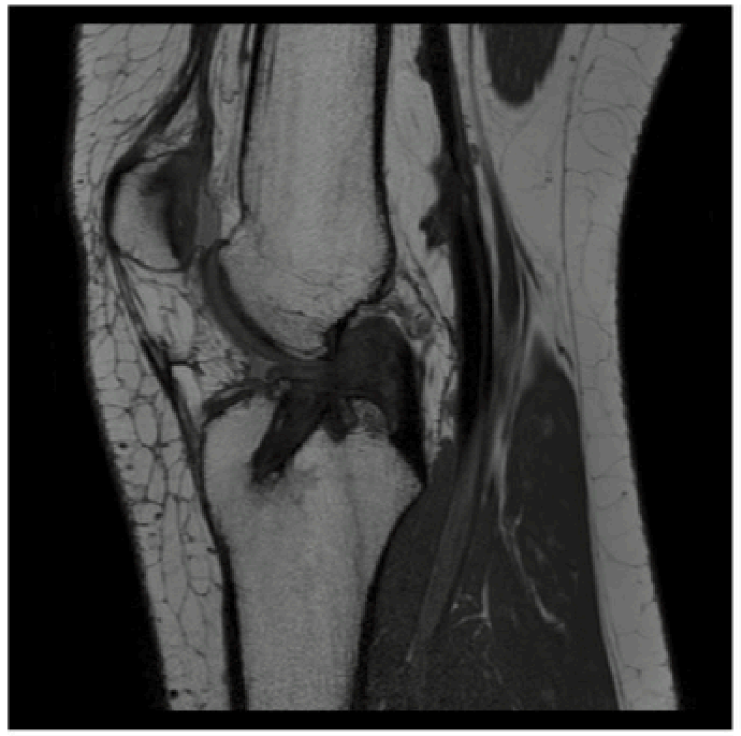
Multi-Sequence 3D Semantic Segmentation

- **Architecture:**
  - **3D sampling pattern** with **encoder-decoder structure**
  - Trained on **multiple pulse sequences** as input channel: **T1 TSE**, **PD TSE**, **PD FS TSE**, **Angio GE**
- **Capabilities:**
  - Automatic segmentation of **13 distinct anatomical** classes:
    - PCL, ACL, cartilage, tendons, arteries, nerves, muscle
- **Key Finding:**
  - Best performance with all **four sequences** (T1PDFSAngio)
  - Confirms **multiple weightings enhance feature learning**
- **Clinical Applications:**
  - **Post & Pre-surgical visualization** (tibial drill holes, intra-articular grafts)
  - 3D **rendering and holographic modeling**
  - Complete knee joint visualization with **transparent adipose tissue**

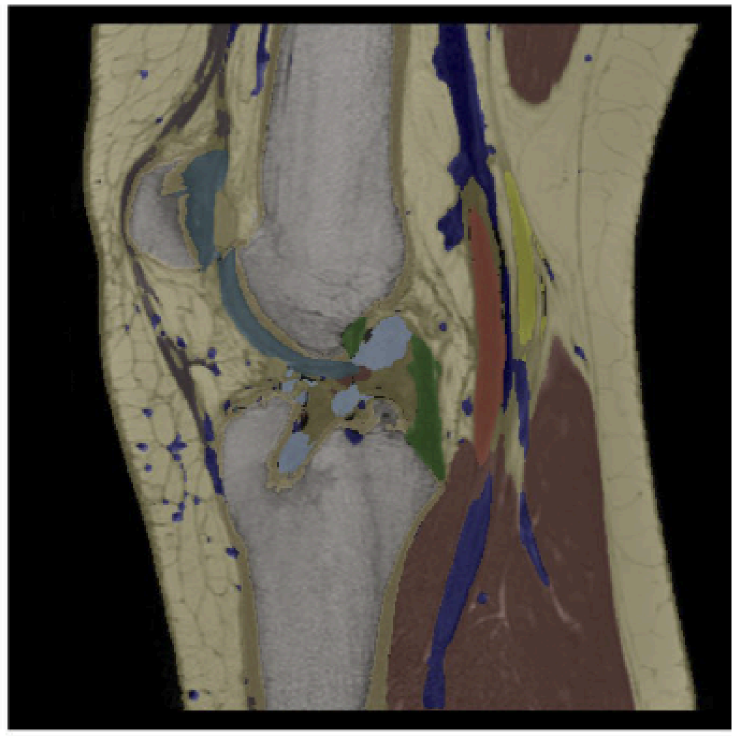
3D DenseVNet

Multi-Sequence 3D Semantic Segmentation

(a) Post-surgical proton density fat suppressed TSE (FS TSE) sagittal plane image showing the torn ACL



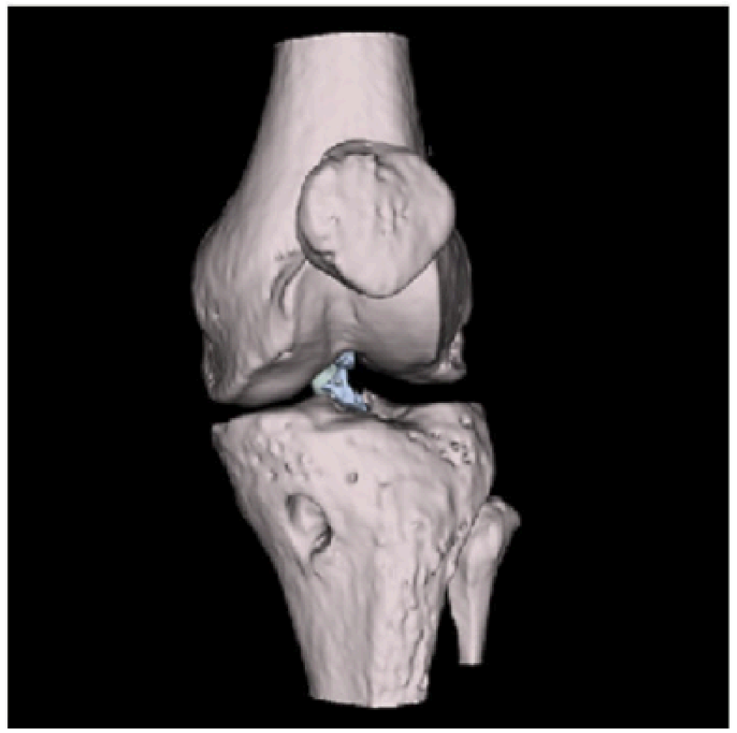
(a)



(b)

(b) Predicted output by the neural network. The tibial drill hole and the intra-articular graft from the reconstructive surgery is visible.

(c) 3D render of the segmentation



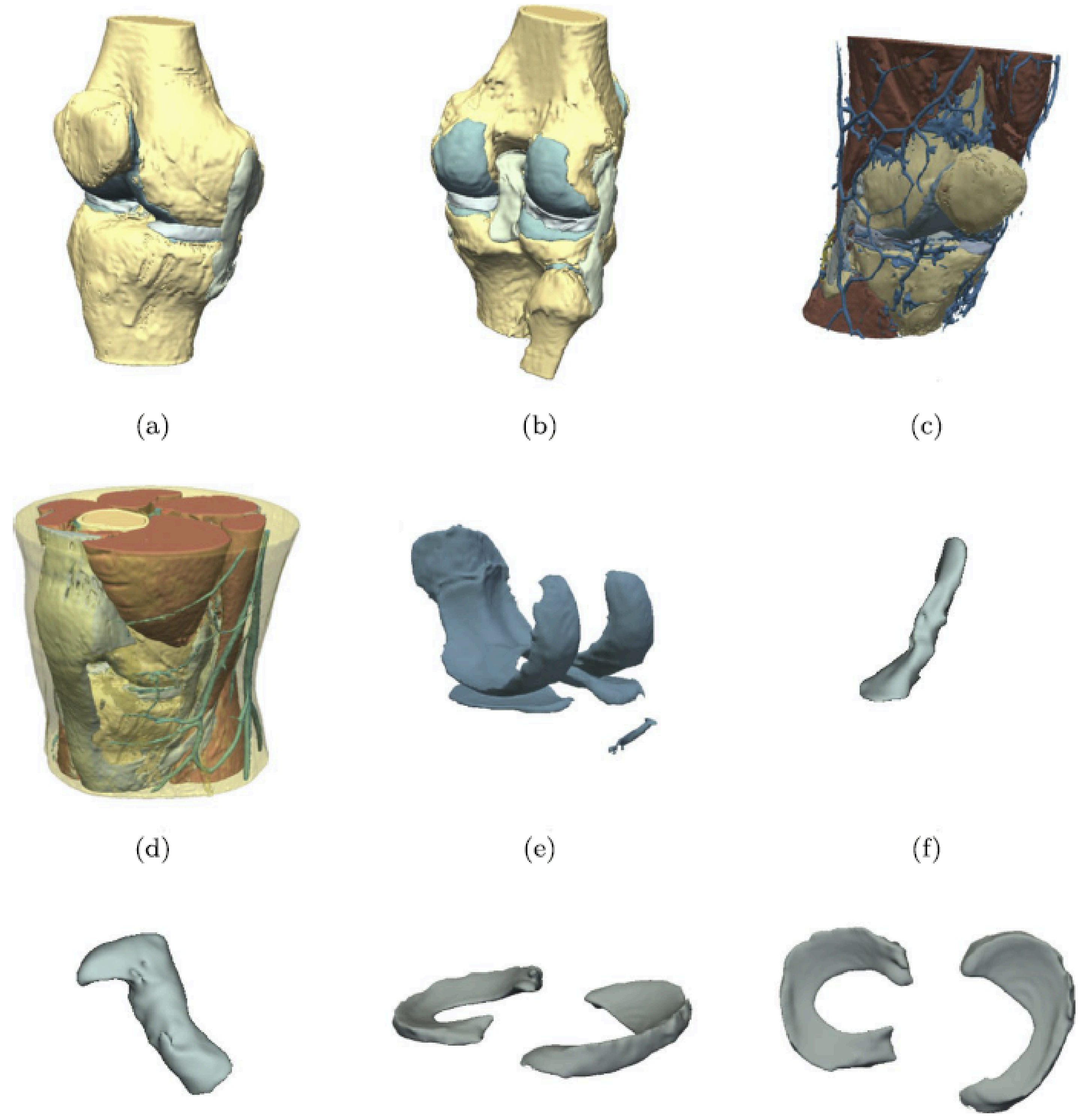
(c)

(d)

(d) Holographic 3D model representation

3D DenseVNet

Multi-Sequence 3D Semantic Segmentation

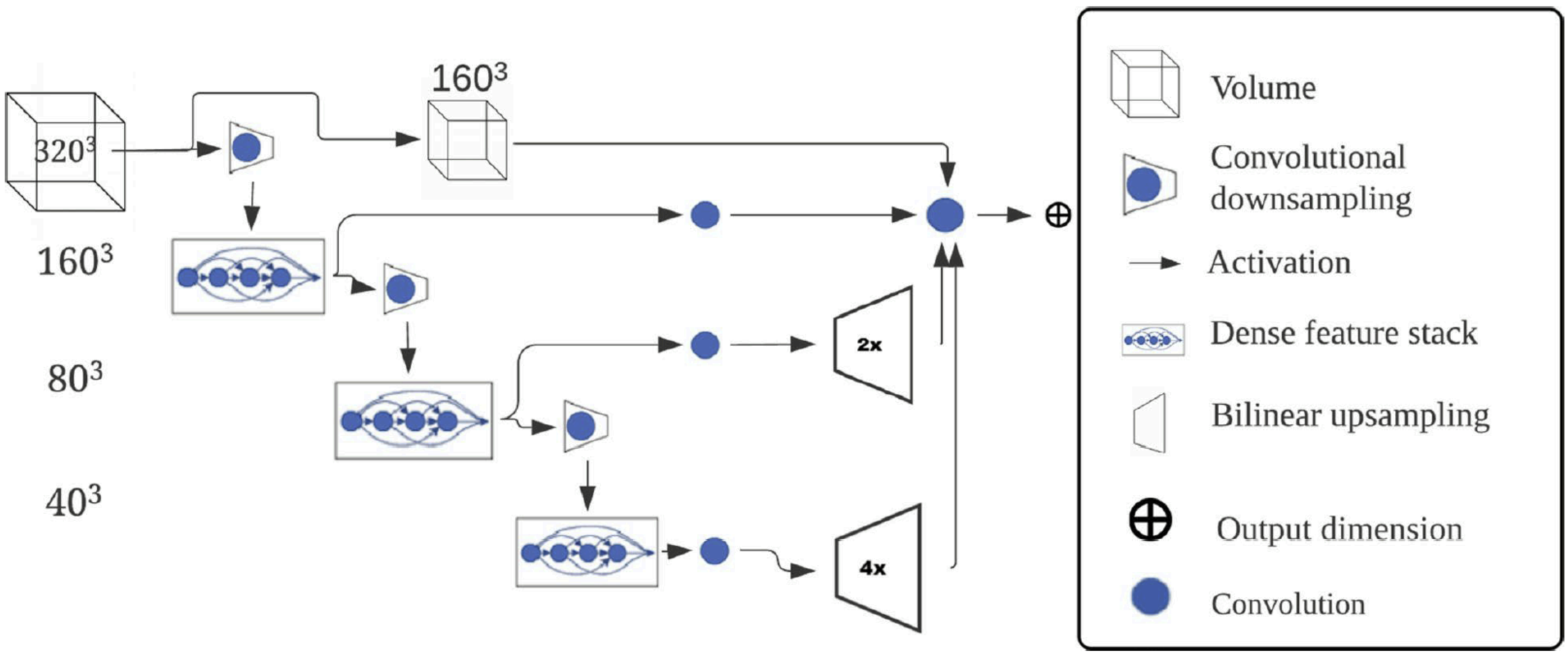


(a) (b) (c) (d) (e) (f) (g) (h) (i)

Results of test dataset in 3D
(a), (b) Bone, ACL, PCL, meniscus and collateral ligaments
(c) Bone, muscles, ligaments and veins
(d) Complete segmentation with transparent adipose tissue
(e) Cartilage
(f) ACL
(g) PCL
(h), (i) Meniscus

3D DenseVNet

Multi-Sequence 3D Semantic Segmentation

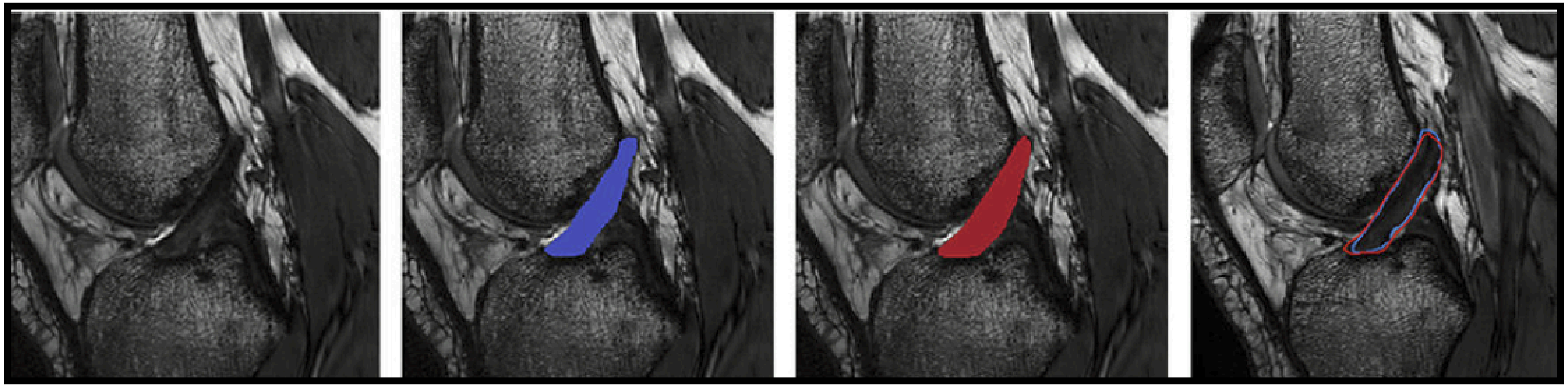


The neural network architecture

Modified 2D U_Net FCNN

Ultra-Fast Automated Segmentation

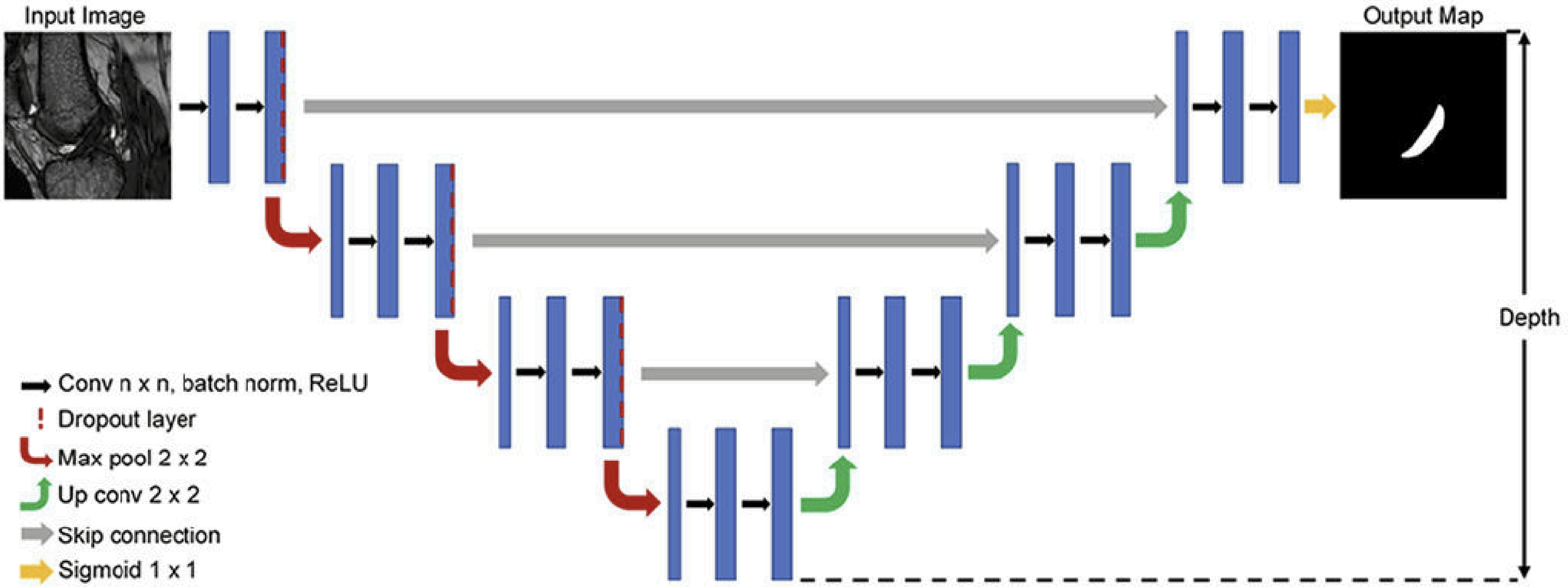
- **Architecture:**
  - FCNN based on U-Net
- **Performance Breakthrough:**
  - Manual segmentation: 1-2 hours per subject
  - Automated segmentation: 0.33 seconds per subject
- **Impact:**
  - Eliminates major bottleneck (time-consuming process of segmentation) in clinical workflow
  - Enables real-time segmentation during MRI reading



MR Image Ground Truth Prediction Contours Overlay

Modified 2D U_Net FCNN

Ultra-Fast Automated Segmentation



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Example modified 2D U-Net architecture (note: final model depth was tuned as hyperparameter).

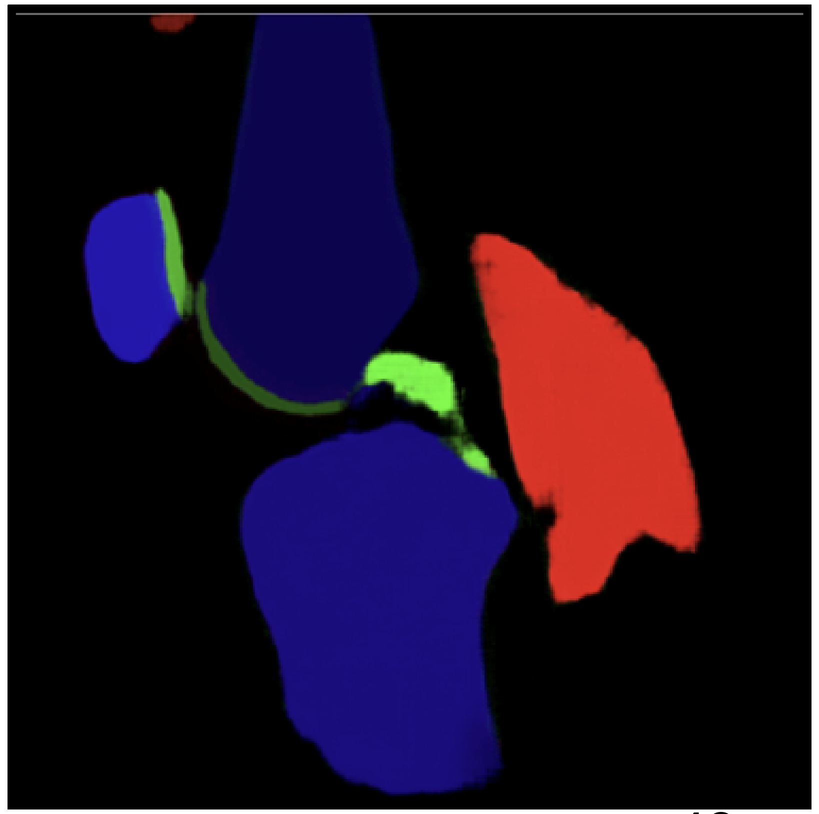
Conditional Generative Adversarial Networks (cGANs)

Adversarial Learning for Multi-Tissue Segmentation

- **Architecture** (Based on **pix2pix** framework):
  - **Generator (G):** Modified U-Net encoder-decoder
  - **Discriminator (D):** PatchGAN (patch-based FCN)
- **Loss Function:**
  - cGAN loss + pixel-wise error loss
  - Ensures **output fidelity** and **reduces blurring**
- **Segmentation Targets:**
  - Femoral, tibial, and patellar bones
  - Cartilage surfaces
  - Cruciate ligaments
  - Selective muscles: medial vastus and gastrocnemius
- **Advantage:** Generates realistic, high-fidelity segmentation masks

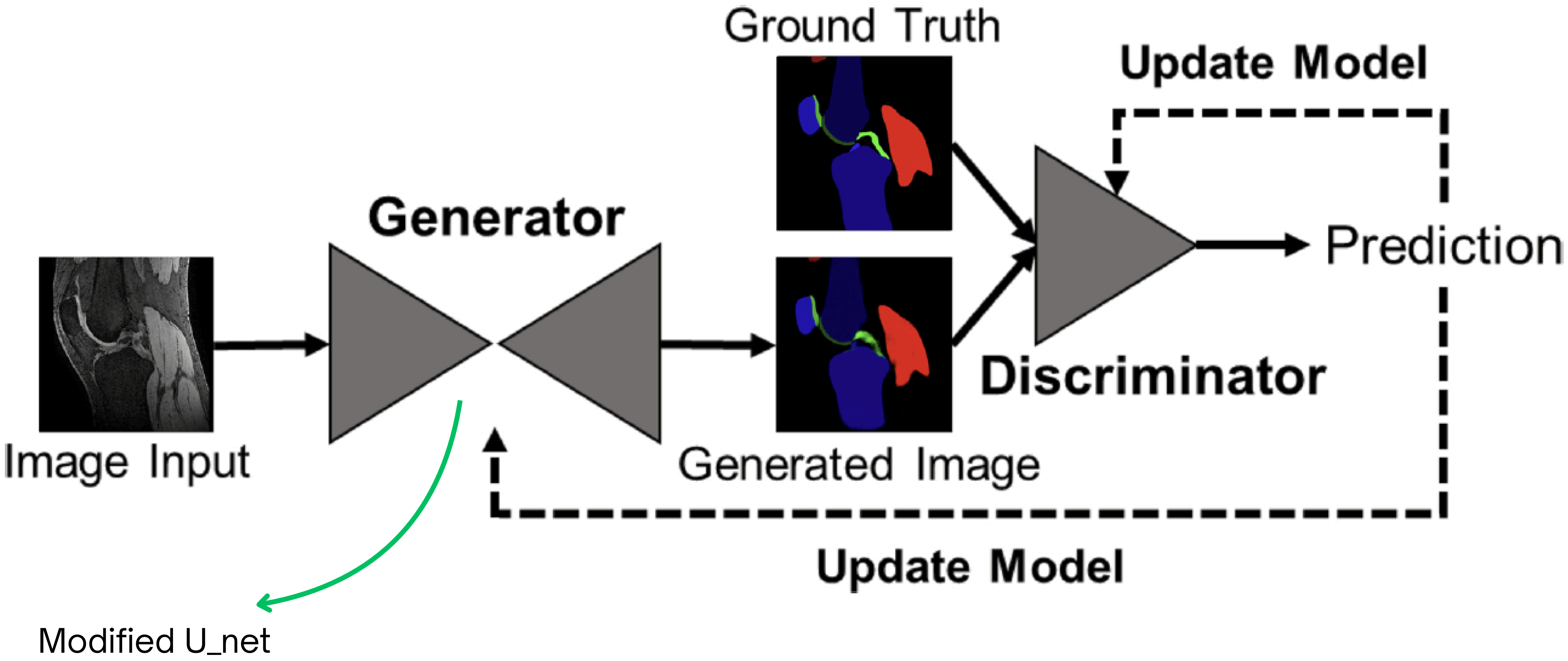
Source Image

PatchGAN output with 1*1 field size



Conditional Generative Adversarial Networks (cGANs)

Adversarial Learning for Multi-Tissue Segmentation



Overview of cGANs architecture

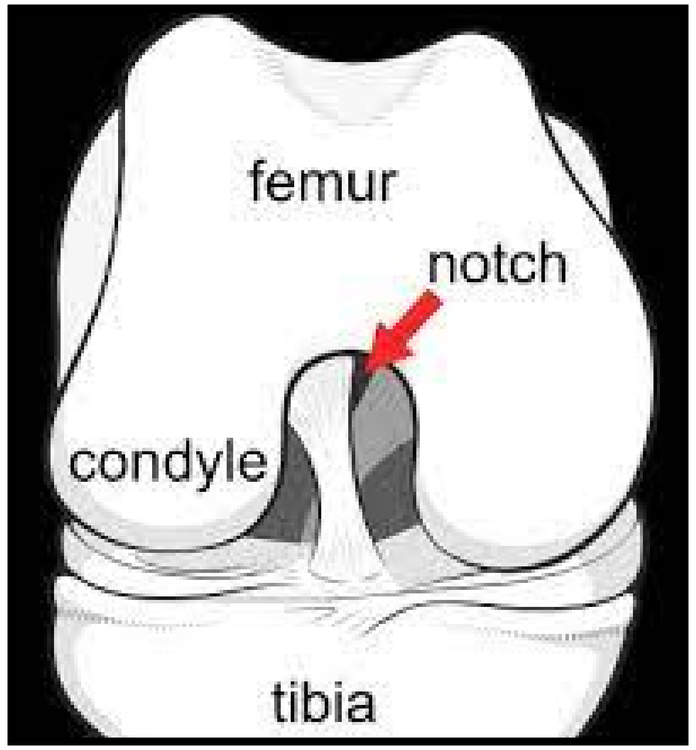
Category 2: Detection & Localization Systems

Pinpointing ACL Tears with Precision

- **Focus:** Identifying **ACL** presence, location, and precise tear sites within the ligament structure

- **Key Applications:**
  - **Slice selection** (filtering ACL-containing images)
  - **ROI isolation** (narrowing focus to intercondylar notch)
  - **Rupture site classification** (femoral side, middle, tibial side)
  - Automated **landmark detection**

- **Clinical Value:**
  - Reduces radiologist workload by **filtering irrelevant images**
  - **Provides surgical guidance for graft placement**
  - Enables **precise documentation of injury location**



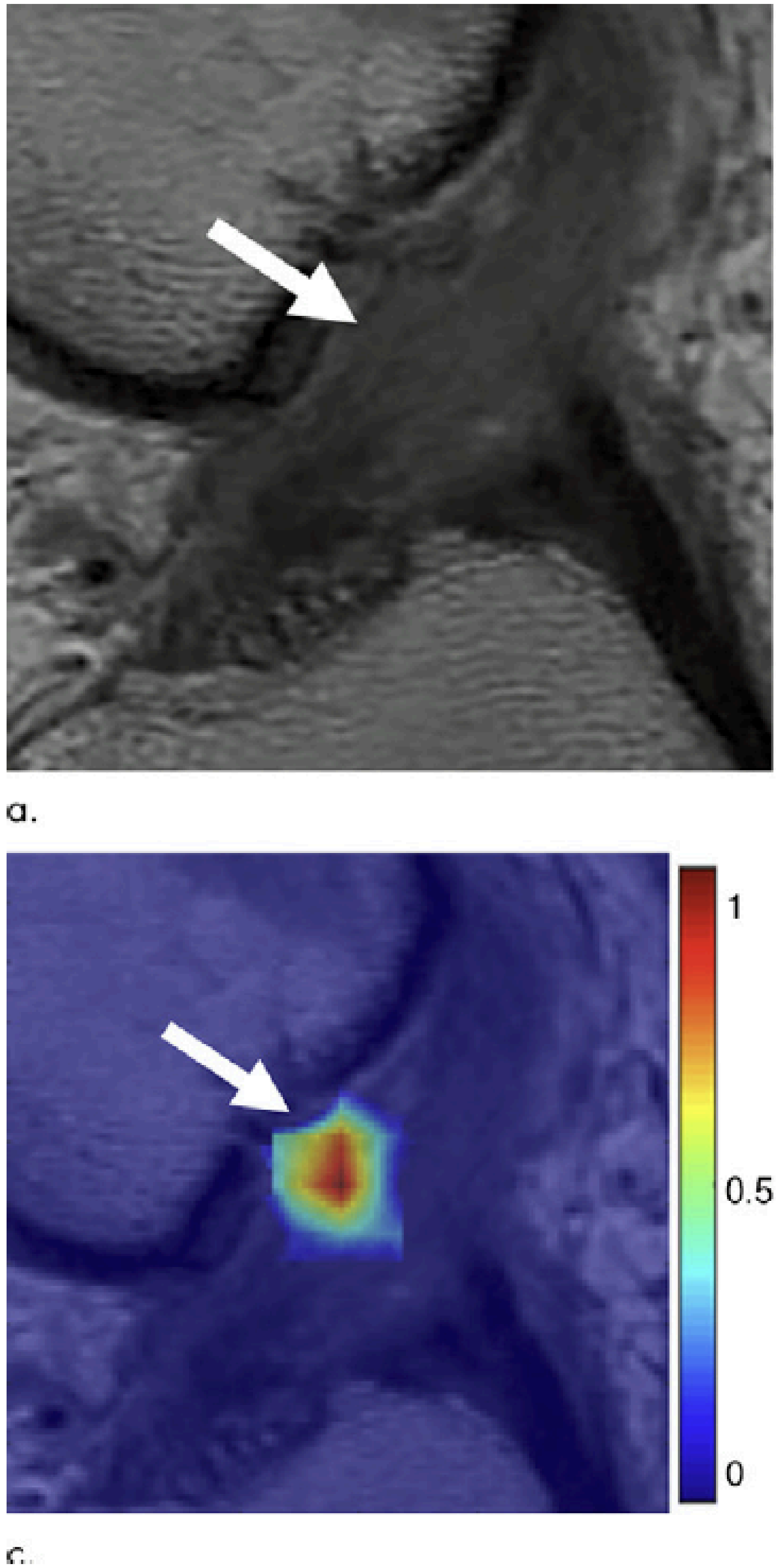
Cascaded Detection with 3 CNNs

Modular Three-Stage Pipeline

- **Three-Stage Process:**
  - Slice Detection (LeNet): Identifies ACL-containing images
  - Ligament Isolation (YOLO): Narrows to intercondylar notch ROI
  - Classification (DenseNet): Determines intact vs. torn

- **Design Philosophy:**
  - Highly modular cascaded structure
  - Emphasizes **precise localization before classification**
  - **Filters superfluous data** to enhance recognition accuracy

- **Outputs:**
  - Diagnosis result (Intact/Torn ACL)
  - Diagnosis probability map



Example of original image and its probability map of an ACL tear

Cascaded Detection with 3 CNNs

Modular Three-Stage Pipeline

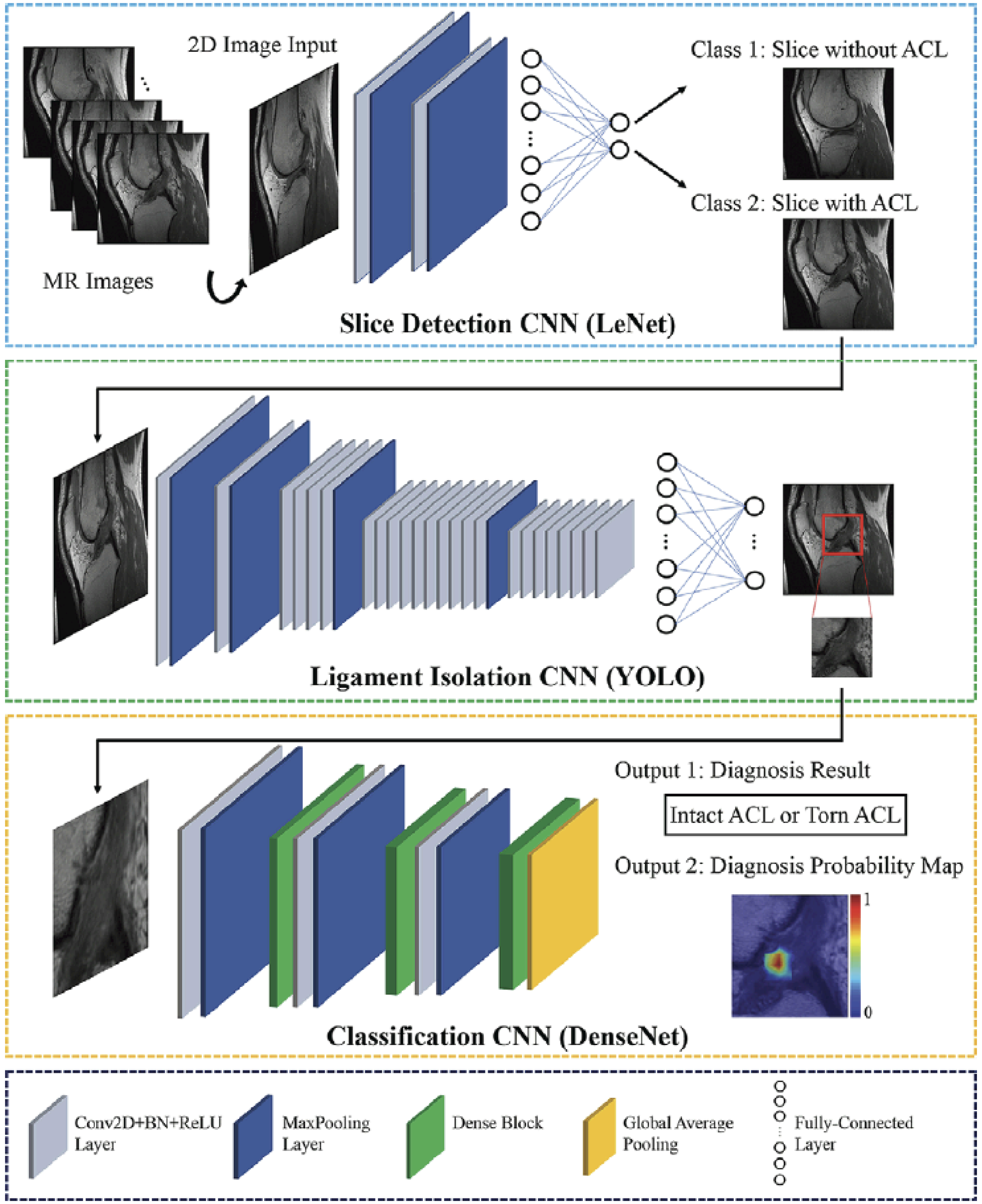


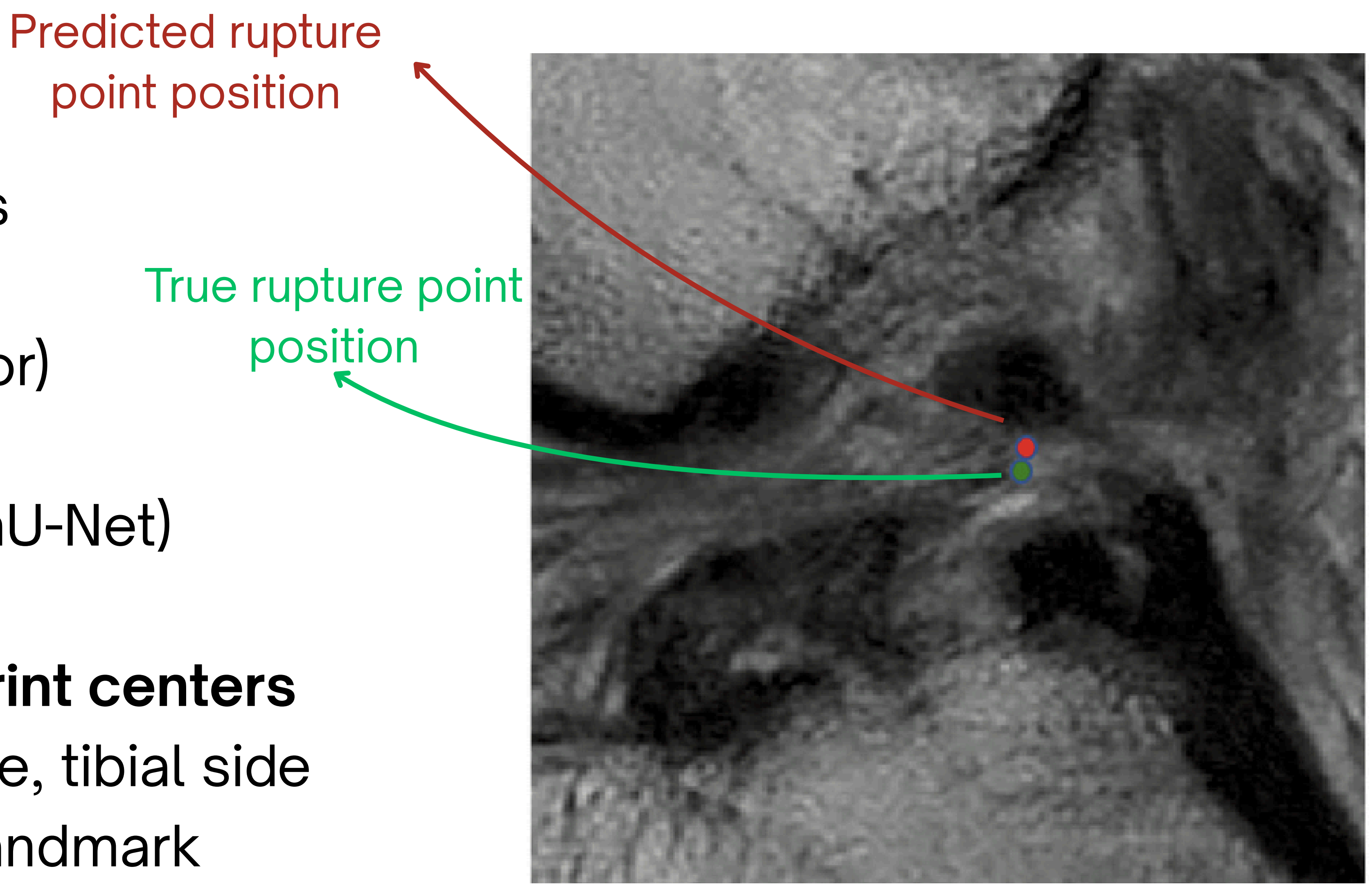
Illustration of the CNN architecture for the deep learning–based ACL tear detection system

3D CNN Scheme for Rupture Localization

Two-Step Segmentation and Landmark Detection

- **Step 1: Coarse Localization (Segmentation)**
  - 3D U-Net architecture
  - Categorizes knee into 4 components:
    - Femur, tibia, femoral footprints, tibial footprints
- **Step 2: Fine Localization & Classification**
  - 3D Full CNN based on YOLOF (single-level detector)
  - ResNet-101 backbone
  - Heatmap regression network (adapted from 3D nnU-Net)
- **Classification Method:**
  - Projects rupture point onto **line connecting footprint centers**
  - Divides into **three equal parts**: femoral side, middle, tibial side

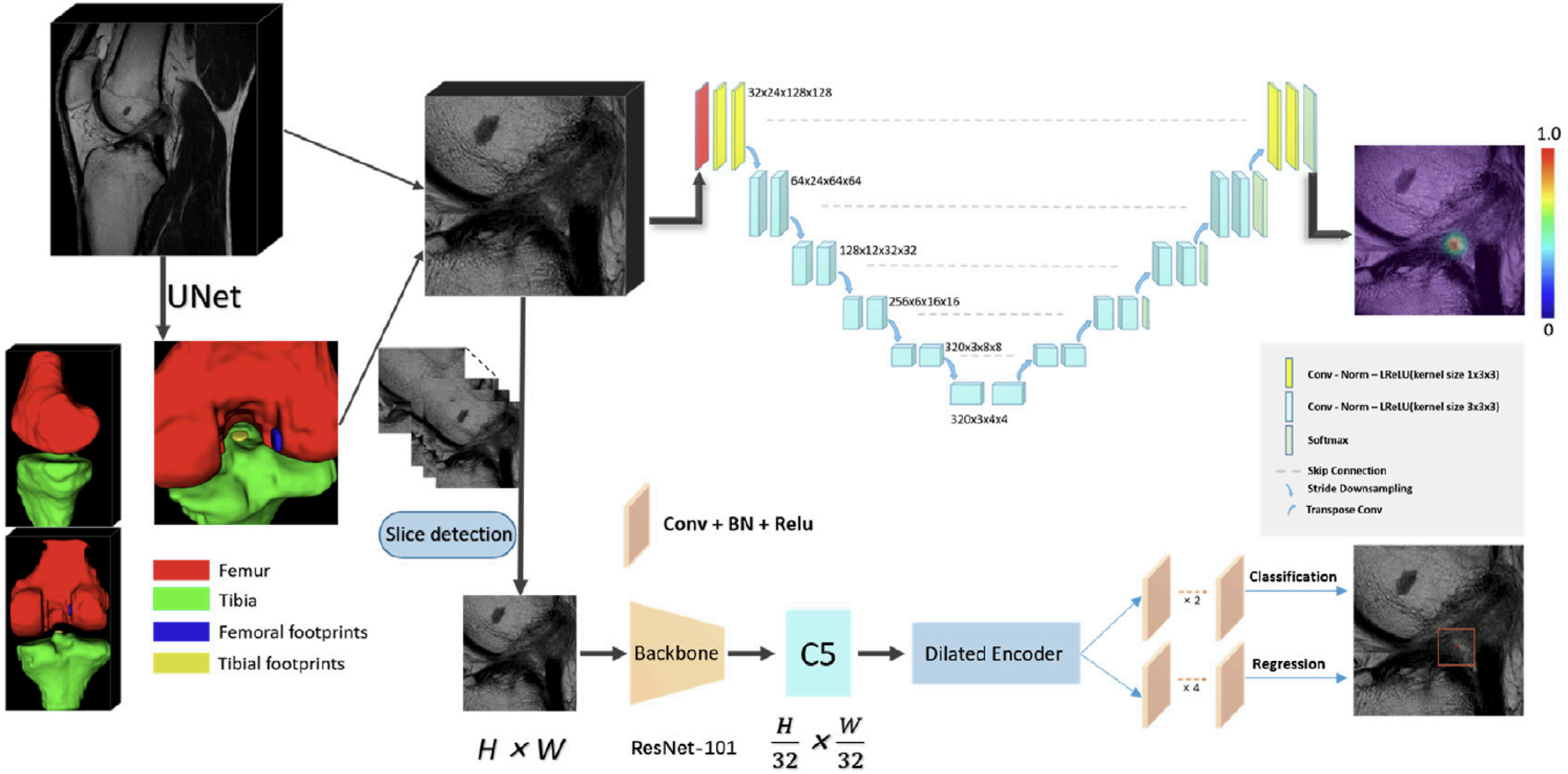
Also includes 2D CNN scheme with slice selection and landmark localization



An example of the model output

3D CNN Scheme for Rupture Localization

Two-Step Segmentation and Landmark Detection



The CNN pipeline for the deep learning-based fully automated ACL rupture localization system

Category 3: Multi-Class Grading & Severity Assessment

Comprehensive WORMS-Based Staging (Whole-Organ Magnetic Resonance Imaging Score)

- **Focus:** Moving beyond **binary classification** to **multi-level severity grading** across multiple knee structures

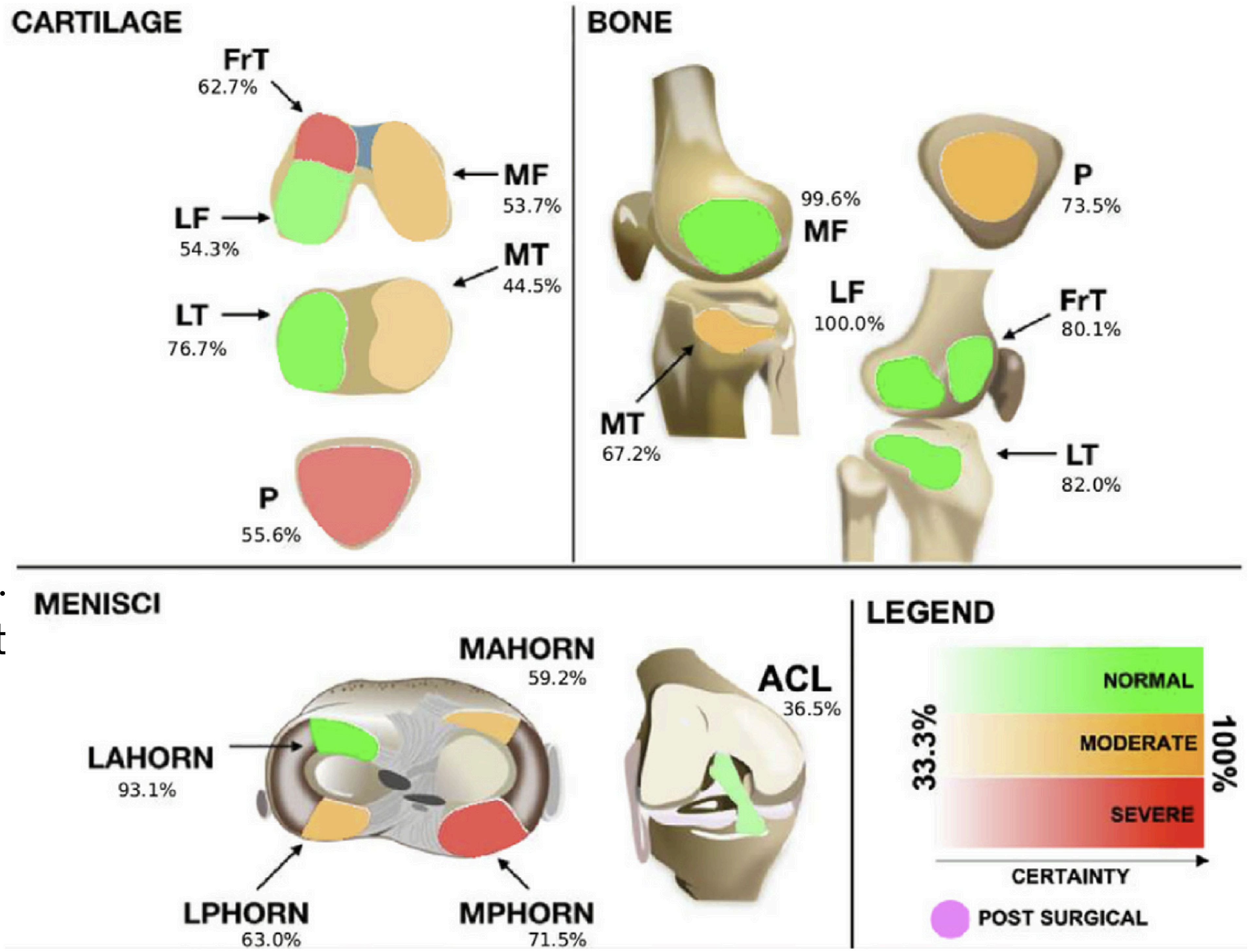
- **Key Applications:**
  - WORMS-based severity staging (cartilage, bone, meniscus, ACL)
  - **Grade-specific treatment** planning
  - Standardized reporting aligned with clinical scales
  - Interreader agreement improvement

- **Clinical Value:**
  - Provides **nuanced diagnostic information**
  - Improves communication between radiologists
  - Supports **evidence-based treatment decisions**
  - **Confidence visualization reduces radiologist overload**

Hierarchic 3D CNN Grading

Multi-Class WORMS Severity Staging with AI Assistance

- **Scope:**
  - Full-knee 3D MRI processing
  - Hierarchic 3D Convolutional Classifiers
  - WORMS-based staging
- **Clinical Impact:**
  - AI boosts interreader agreement:
    - Cohen's κ: **0.42 (weak)** → **0.61 (moderate)**
  - GUI displays confidence levels **(color + transparency)**



Colors indicate the lesion class:
red: severe | orange: moderate (or mild) | green: no lesion.
Transparency: the probability output by the model for that class (stronger colors → more confidence)
The ACL, when deemed reconstructed, is set to a differentiated color with no transparency level and is indicated as being postsurgical.

Hierarchic 3D CNN Grading

Multi-Class WORMS Severity Staging with AI Assistance

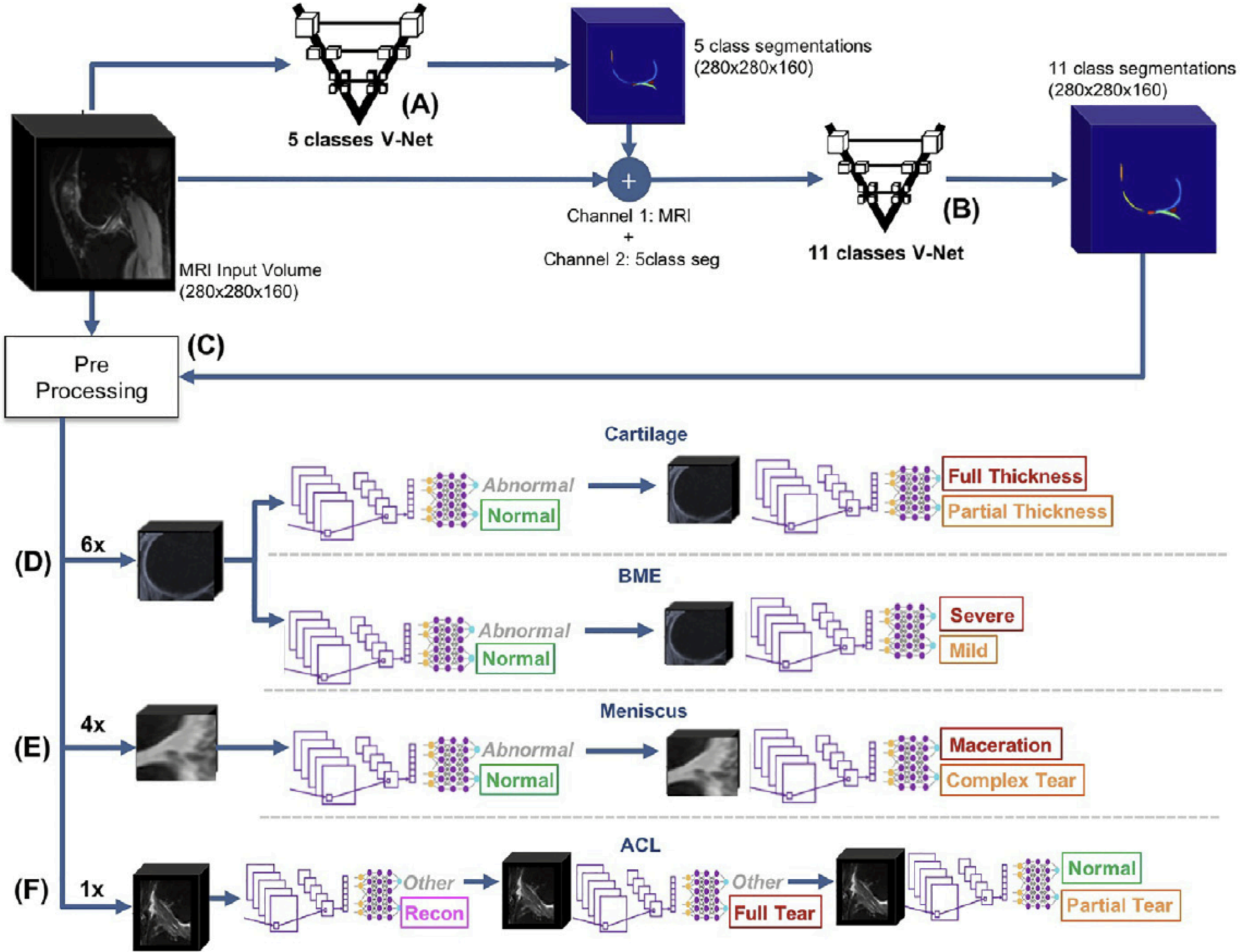
Pipeline (4 Stages):

A. 5-class cartilage compartment segmentation (V-Net)

B. 11-class segmentation with original image + 5-class input

C. ROI extraction with volumetric bounding boxes

D-F. 17 3D CNNs → 52 probabilities for all lesion types

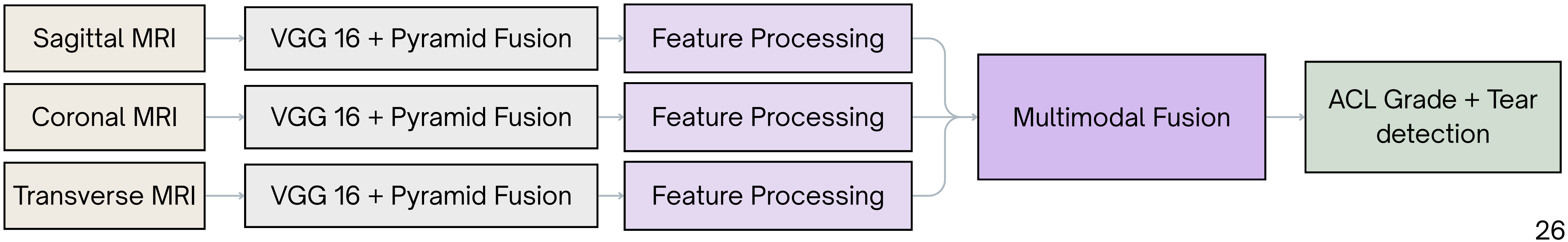


Recon = Reconstruction

Multi-Plane Efficacy and Grading

Four-Grade ACL Injury Classification

- **Grading System:**
  - **Grade 0:** No abnormalities
  - **Grade I:** Good continuity, intact contour, <50% damage (Small signal patches/streaks, slightly thickened)
  - **Grade II:** Poor continuity, some fibers visible, ⩾50% damage (Local/diffuse thickening, incomplete edges, high signal)
  - **Grade III:** Complete rupture, broken continuity (Displaced/bent ends, clumped ligament, unclear boundaries)
- Model Architecture:



Category 4: Advanced Architecture Approaches

Innovative Network Designs for Enhanced Performance

- **Focus:** Developing **high-performance models** with **minimal training data**

- **Key Innovations:**
  - **Attention mechanisms** for capturing **multi-scale relationships**
  - **Graph Convolutional Networks** for **spatial dependencies**
  - **Self-supervised contrastive learning**
  - **Hybrid attention modules** (layer, channel, space scales)

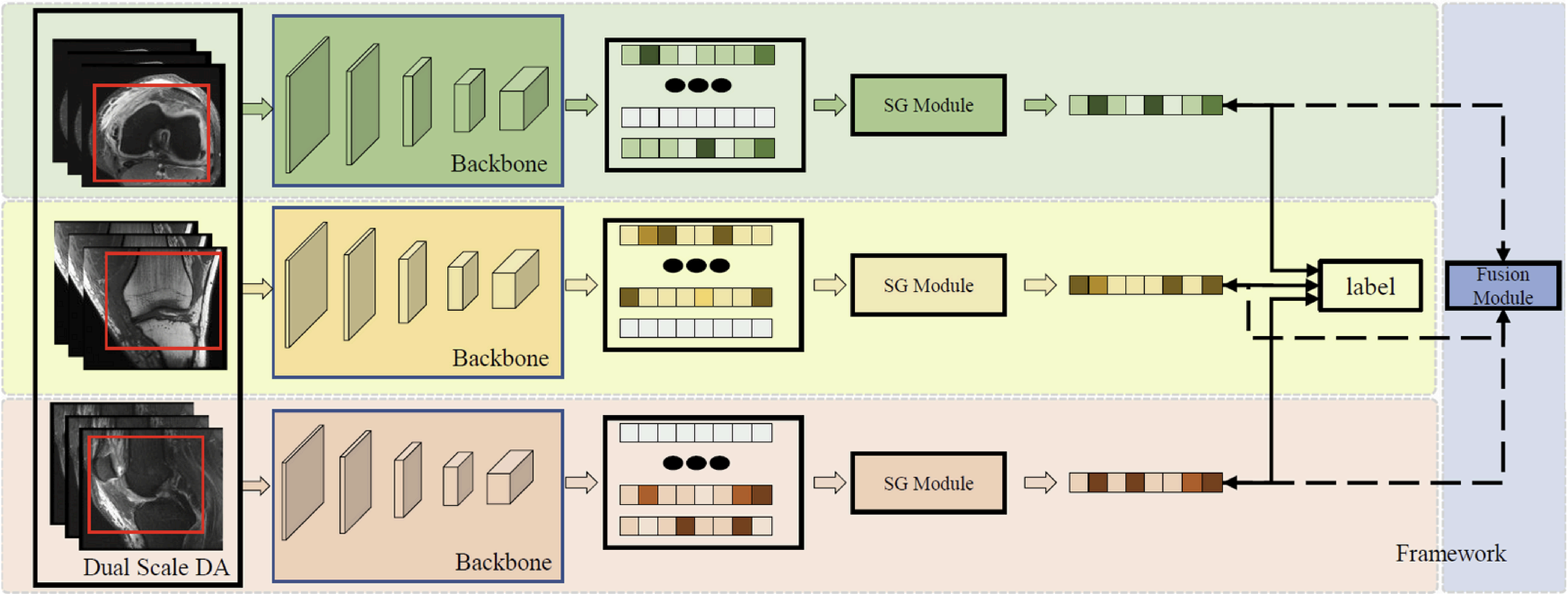
- **Clinical Value:**
  - Improved accuracy through better feature representation
  - Faster inference times (down to **0.5s per scan**)
  - Reduced false positives and false negatives

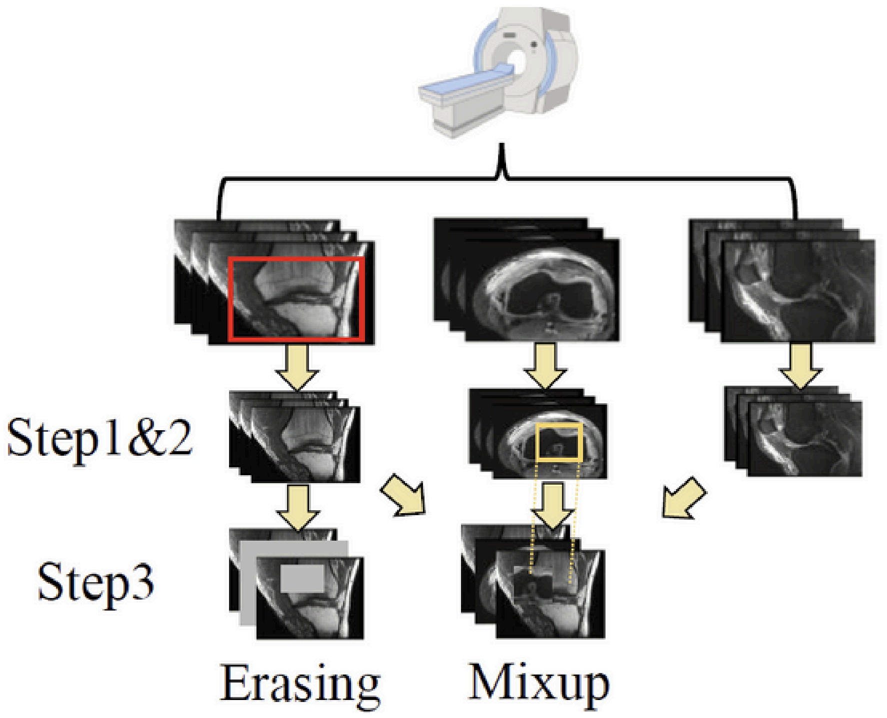
SGNET

Selective Group Attention Network

- **Design Philosophy:** Mimics clinical diagnosis workflow
- **Three Key Modules:**
  - 1. **Dual-Scale Data Augmentation (DDA):** Enriches training data on **spatial & layer scales**
  - 2. **Selective Group Attention (SG):** Captures **relationships across layer, channel, and space**
  - 3. **Fusion Module:** Explores **inter-relationships** among perspectives | Achieves final classification
- **Advantage:** Multi-scale attention mechanism improves detection of subtle ACL tears

Overview of SGNET model
Backbone is MRNet





The pipeline of data processing. step 1. random crop; step 2. normalization; and step 3. erasing or mixup

KneeXNet

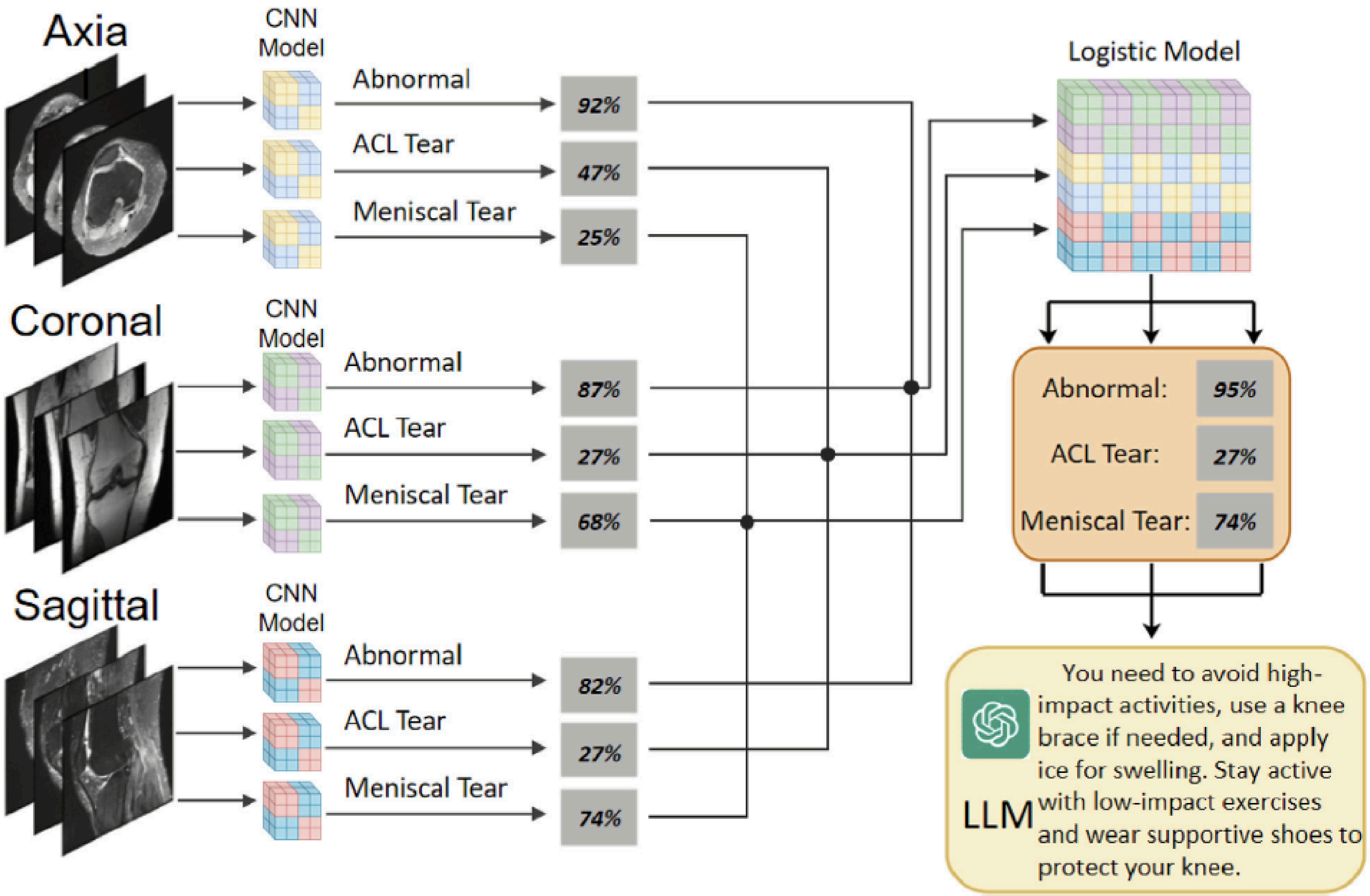
Graph Convolutional Networks for Spatial Dependencies

- **Novel Approach:** Represents knee MRI as a graph
  - **Nodes**: Key anatomical landmarks
  - **Edges**: Spatial connections between these landmarks
- **Three Main Components:**
  - **Graph Construction:** Extracts features from local patches
  - **GCN Layers:** Learn hierarchical features
  - **Multi-Scale Fusion:** Combines features across resolutions
- **Key Innovation:**
  - Self-supervised contrastive learning
  - Positive/negative MRI patch pairs
  - Enhances discriminative/robust representations
- Performance:
  - Rapid: **0.5s** per MRI scan
  - Ablation studies confirm **GCN layers essential for spatial dependencies**

- **Results:**
  - AUC scores: **0.985**
  - ACL tears detection: **0.972**
  - Meniscal tears: **0.968**

KneeXNet

Graph Convolutional Networks for Spatial Dependencies



The overall architecture of KneeXNet

ACGNN

Attentive Graph NN with CRF and Meta-Learning

- **Classification Task:** 6 grades (Types I-V based on tear location + Normal)

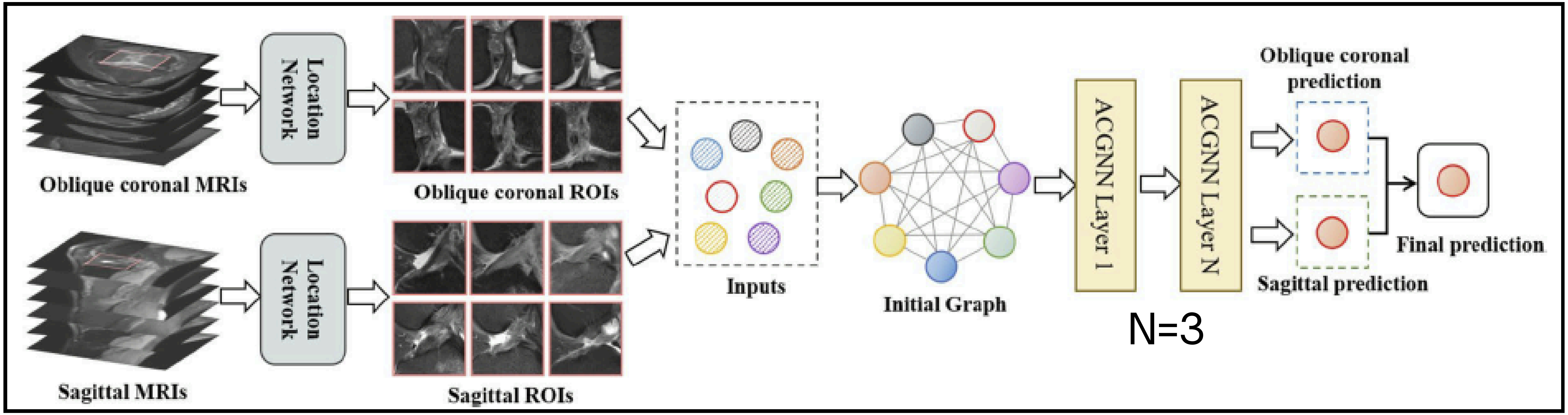
The tear location indicates the **distal remnant length** as percentage **of the ligament length**

Tear Type	Type I	Type II	Type III	Type IV	Type V
Location %	> 90	75-90	25-75	10-25	<10

- **Three Key Innovations:**
  - Lightweight Feature Embedding (**knowledge distillation**):
    - Better accuracy-compute trade-off
  - **CRF** Integration:
    - **Refines sample affinities** in GNN layers
  - **Meta-Learning Strategy**:
    - Fast/accurate classification
    - CRF loss addition boosts accuracy >1%
- **Advantage:** Precise tear location classification guides surgical planning

ACGNN

Attentive Graph NN with CRF and Meta-Learning



Overview of the pipeline of the proposed DL framework

Category 5: Data-Efficient & Few-Shot Learning

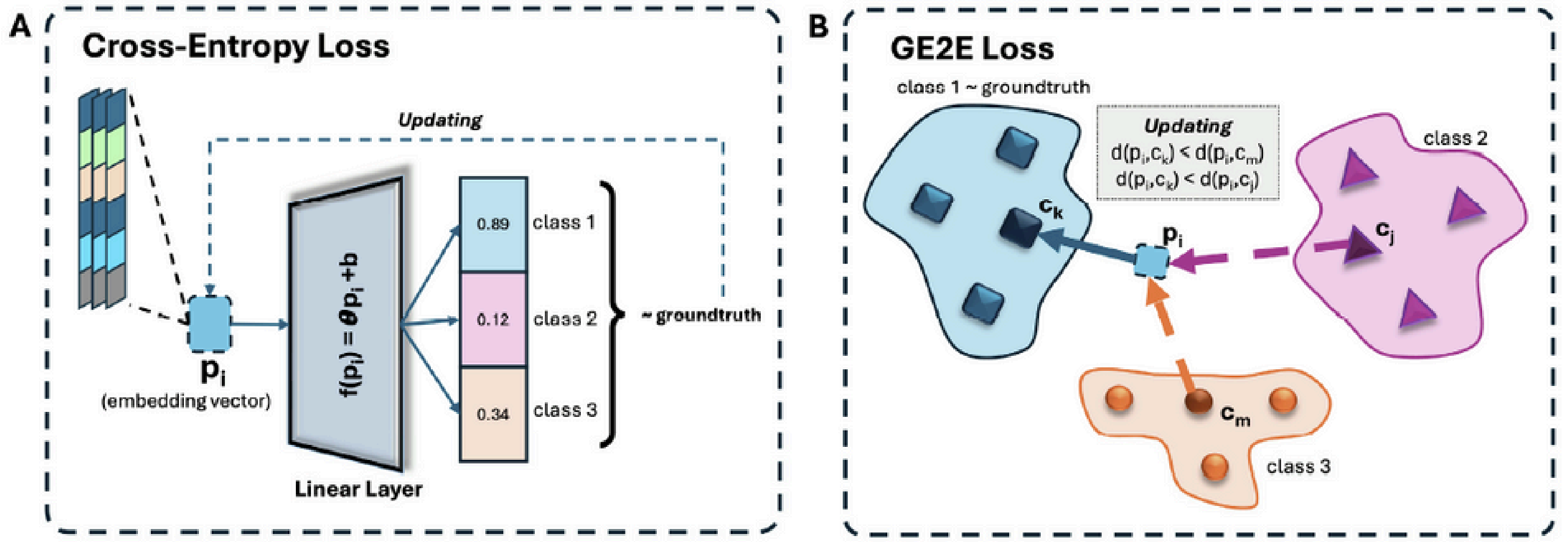
Overcoming Data Scarcity Challenges

- **Focus:** Novel architectural innovations including attention mechanisms, graph networks, and specialized feature extraction
- **Key Challenge:**
  - Medical imaging datasets are **expensive and time-consuming to annotate**
  - **Limited samples for rare pathologies**
  - Need for **specialized**, **site-specific models**
- **Solution Approach:**
  - **Few-Shot Learning (FSL)** frameworks
  - **Metric learning with optimized embedding spaces**
  - **Transfer Learning** (TL) from larger datasets
- **Clinical Value:**
  - Enables deployment in data-scarce clinical settings
  - Faster model development for specialized applications
  - Reduces annotation burden on radiologists

MedNet-FS

3D Few-Shot Learning Framework

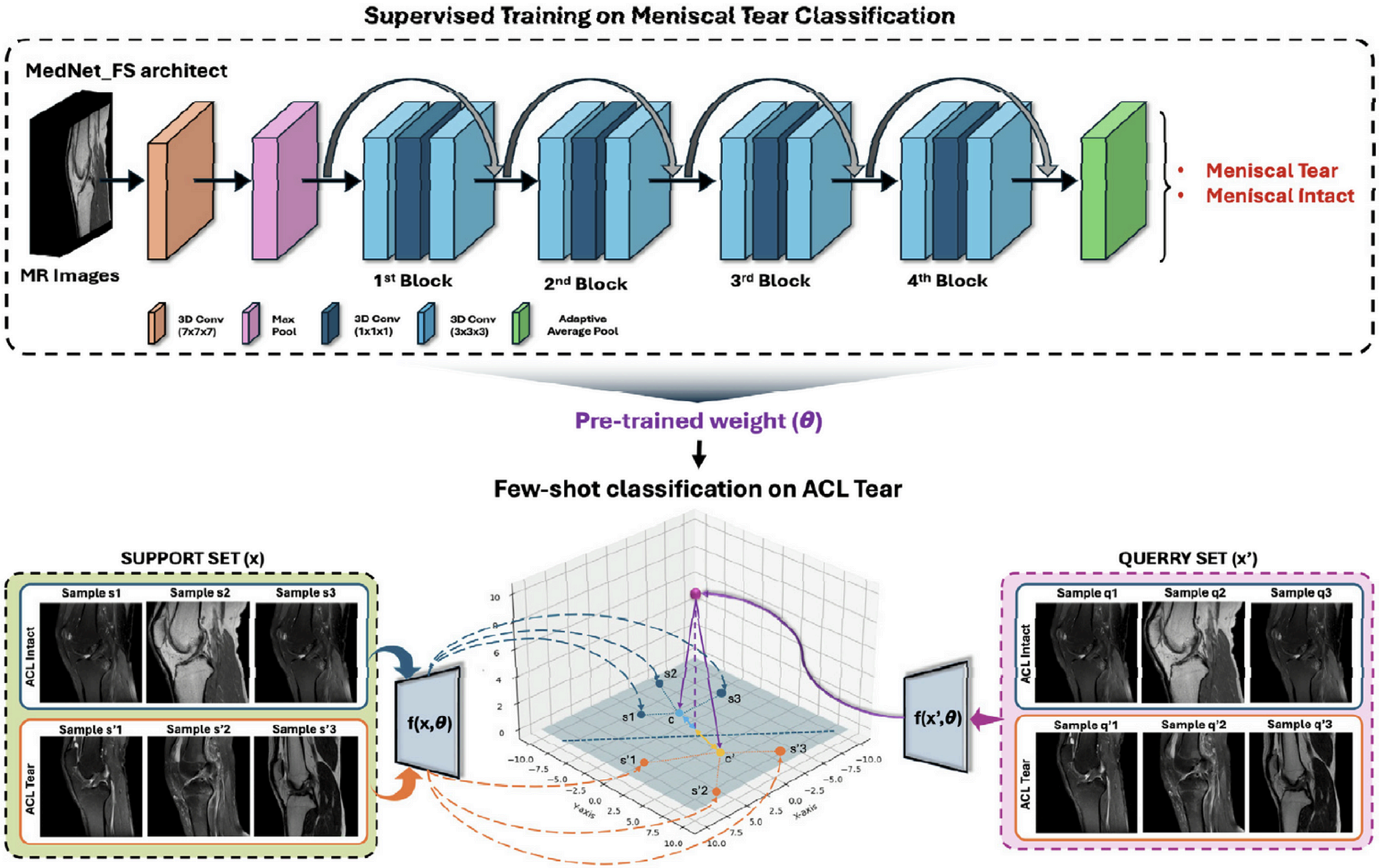
- **Goal:** Substantially reduce data dependency for specialized medical imaging tools
- **Technical Approach:**
  - Few-Shot Algorithm integrated with generalized end-to-end **(GE2E) loss**
  - Optimizes embedding space:
    - ↓ **Intra-class distances** (similar cases closer)
    - ↑ **Inter-class distances** (different cases farther)
    - → More **discriminative features**
- **FSL Concept:**
  - Data-efficient approach for recognizing unseen classes
  - **k-shot task:** learns from k examples per class
- **Performance:**
  - **AUC of 0.76** for ACL tear classification, using only **k=40 samples**
- **Impact:** Demonstrates viability of high-performance models with minimal data



(A) traditional Cross-Entropy Loss; (B) the GE2E Loss, designed to optimize the embedding space

MedNet-FS

3D Few-Shot Learning Framework



Supervised training process with MedNet (ResNet101)

MedNet-FS architecture

Category 6: Multi-Plane & Multi-Task Models

Comprehensive Analysis Through Integration

- **Focus: Leveraging multiple MRI planes** and **simultaneous task execution** for comprehensive diagnosis

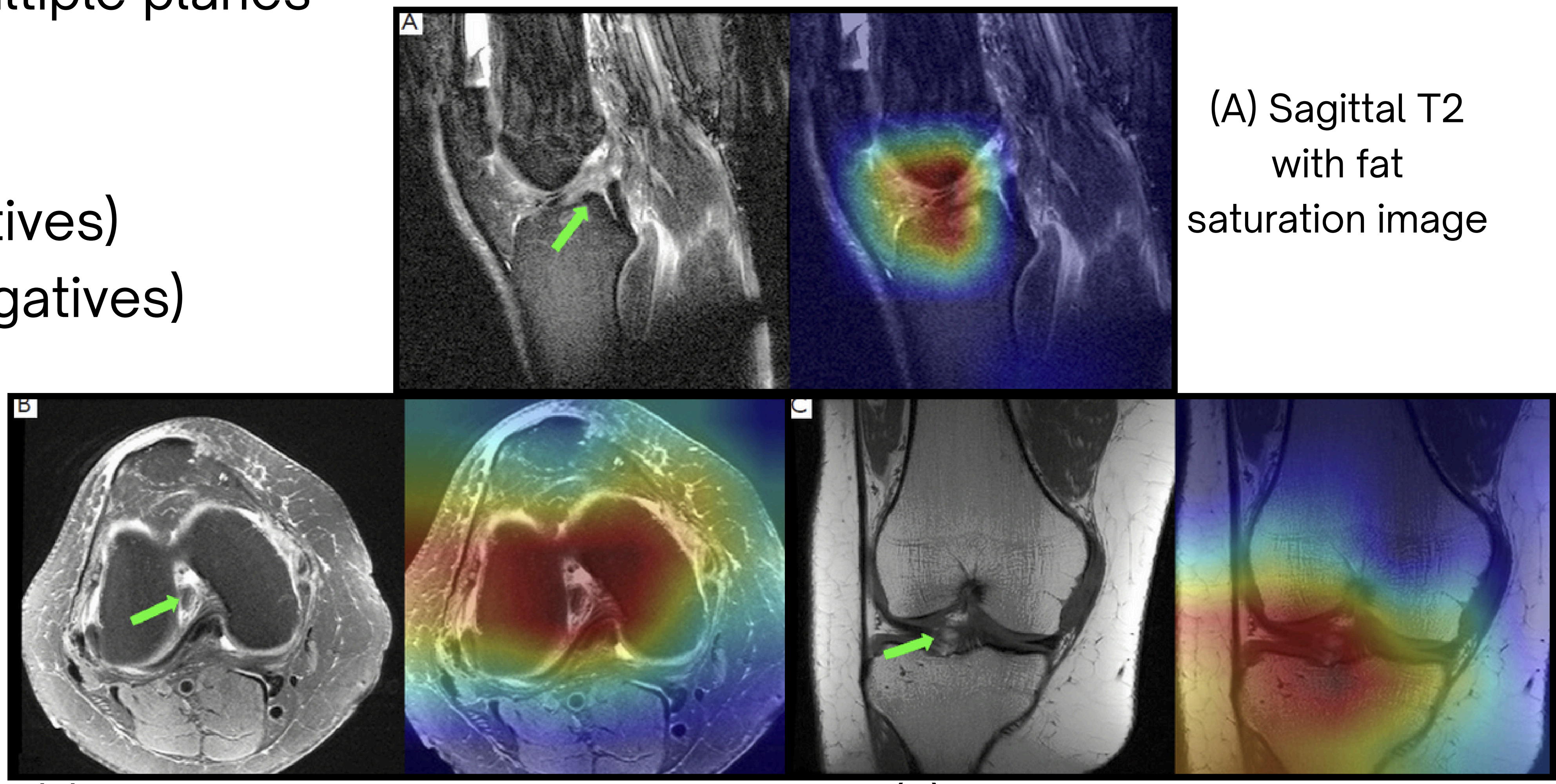
- **Key Approaches:**
  - **Multi-plane fusion** (sagittal, coronal, axial)
  - **Multi-task learning** (segmentation + classification)
  - **Semi-supervised learning** (pseudo-labeling)
  - **Cross-sequence attention mechanisms**

- **Clinical Value:**
  - Mimics radiologist workflow (reviewing multiple planes)
  - Simultaneous diagnosis of multiple abnormalities
  - Improved accuracy through complementary information
  - Reduced false negatives by cross-validating findings

TripleMRNet

Multi-Plane Feature Fusion

- **Capability:** Analyzes 7 flexible combinations of sagittal, coronal, and axial inputs
- **Design Philosophy:**
  - Mimics clinical workflow of synthesizing multiple planes
  - **Feature-level fusion** via **concatenation**
- **Efficiency Metrics (Priority):**
  - F1 Score: Balancing precision (↓ false positives)
  - Recall: Avoiding missed injuries (↓ false negatives)
- **Performance Results:**
  - ACL Tear Detection:
    - Three-plane model: Best performance
      - **Accuracy: 0.925 | F1 Score: 0.919**
  - Meniscal Tears:
    - **Axial plane** surpassed **sagittal plane**



(A) Sagittal T2 with fat saturation image

(B) Axial proton density-weighted image

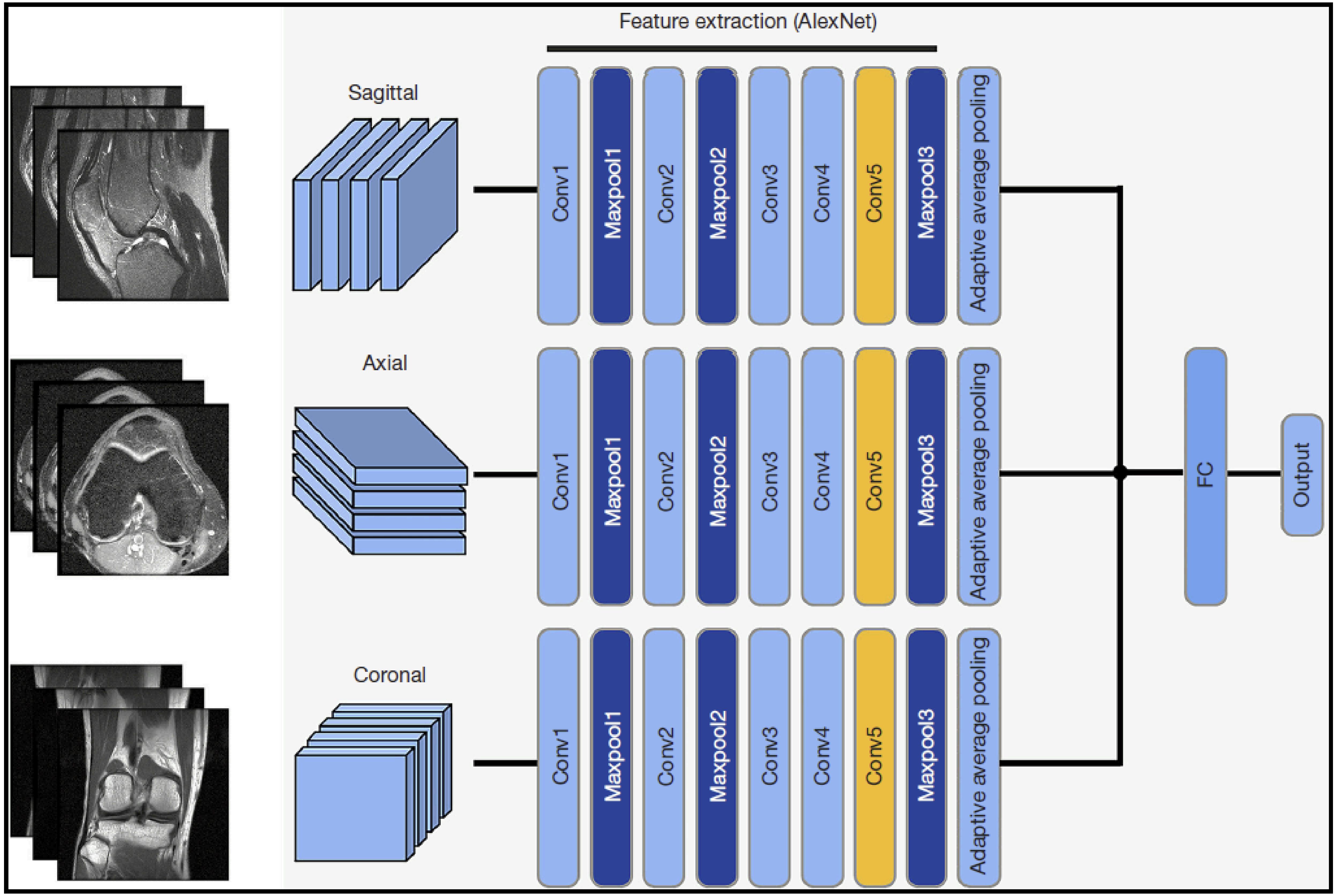
(C) Coronal T1-weighted image

- **Key Finding:** Multi-plane integration provides complementary information

TripleMRNet

Multi-Plane Feature Fusion

The orange border indicates the final convolutional layer computing the **CAM scores** and **generate heatmaps.**



TripleMRNet architecture

CoPAS

Co-Plane Cross-Sequence Attention Network

- **Scope:** Multi-task model for simultaneous diagnosis of **12 knee abnormalities**
- **Technical Innovation:**
  - Generates **synthetic cross-plane volumes**
  - **Integrates via attention mechanism**
  - Captures **spatial correspondence and inter-sequence dependencies**
- **Performance:**
  - Strong generalizability across multiple centers
  - Surpasses SOTA models across all 12 classes
  - Cross-dataset evaluation demonstrates robustness
- **Clinical Impact:**
  - Boosts diagnostic performance for junior AND senior radiologists
  - Serves as effective clinical assistant
  - Class activation maps provide interpretability
- **Advantage:** Comprehensive knee assessment in single forward pass

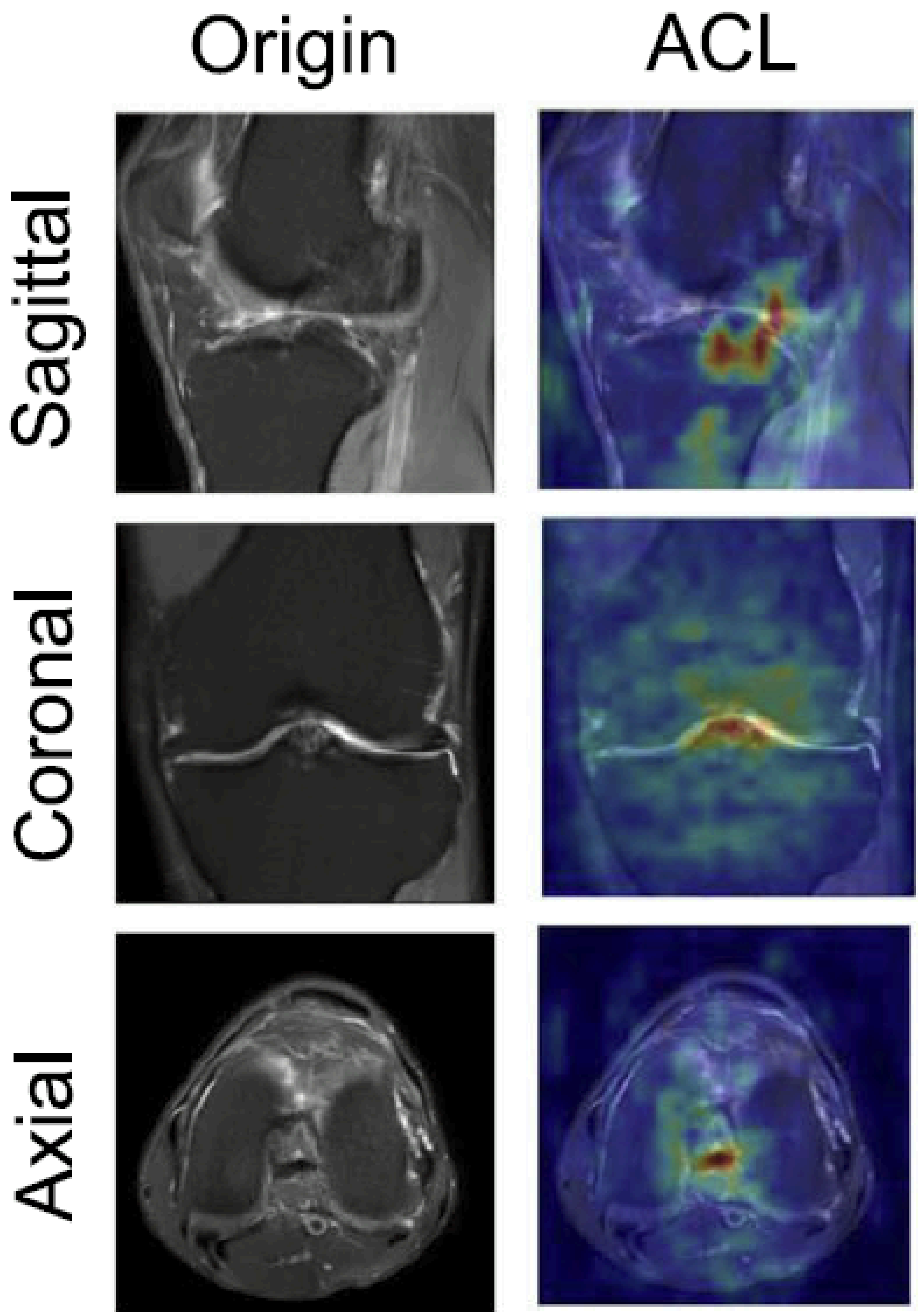
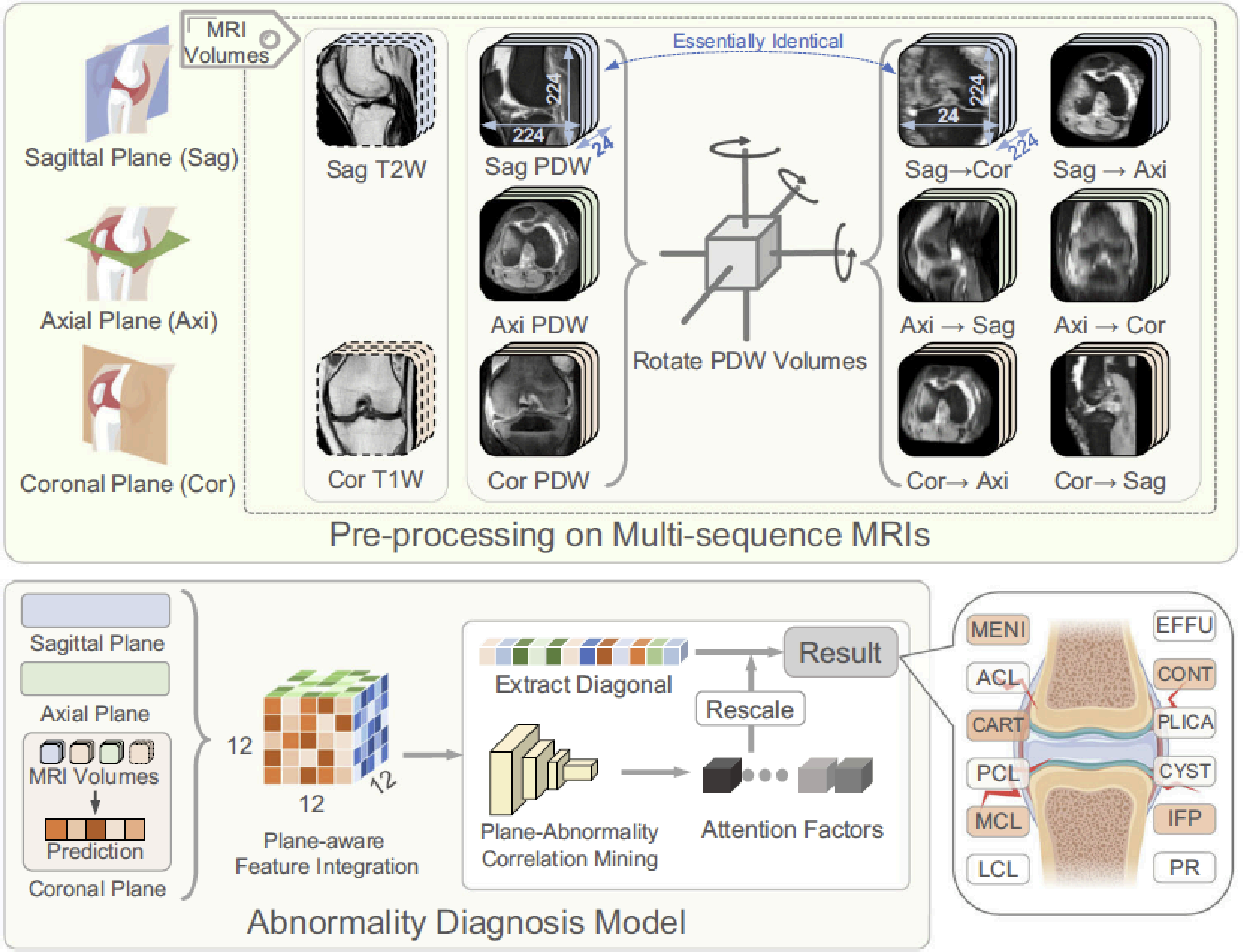


Illustration of class activationmap on a patient with ACL

CoPAS

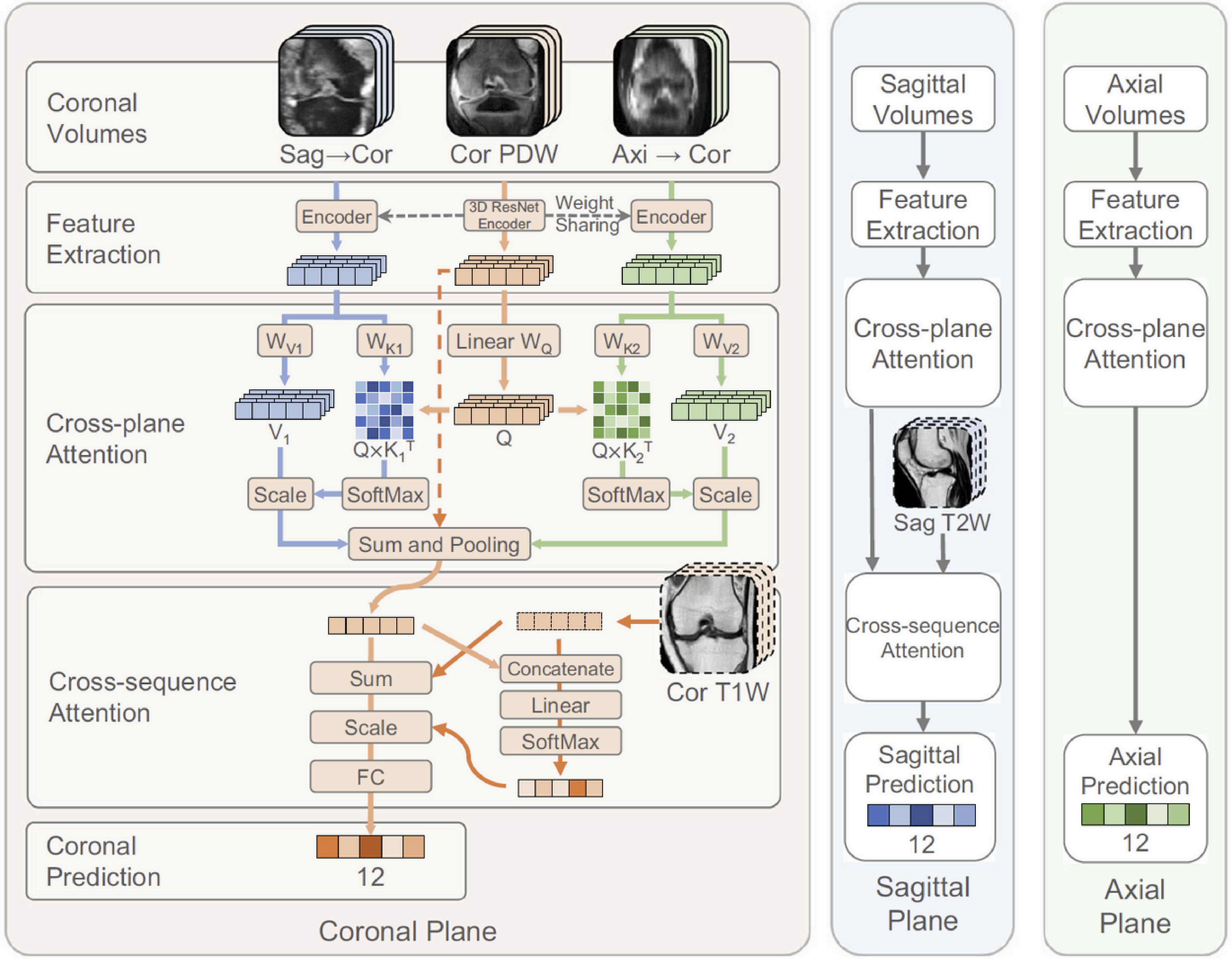
Co-Plane Cross-Sequence Attention Network



The pipeline of CoPAS

CoPAS

Co-Plane Cross-Sequence Attention Network

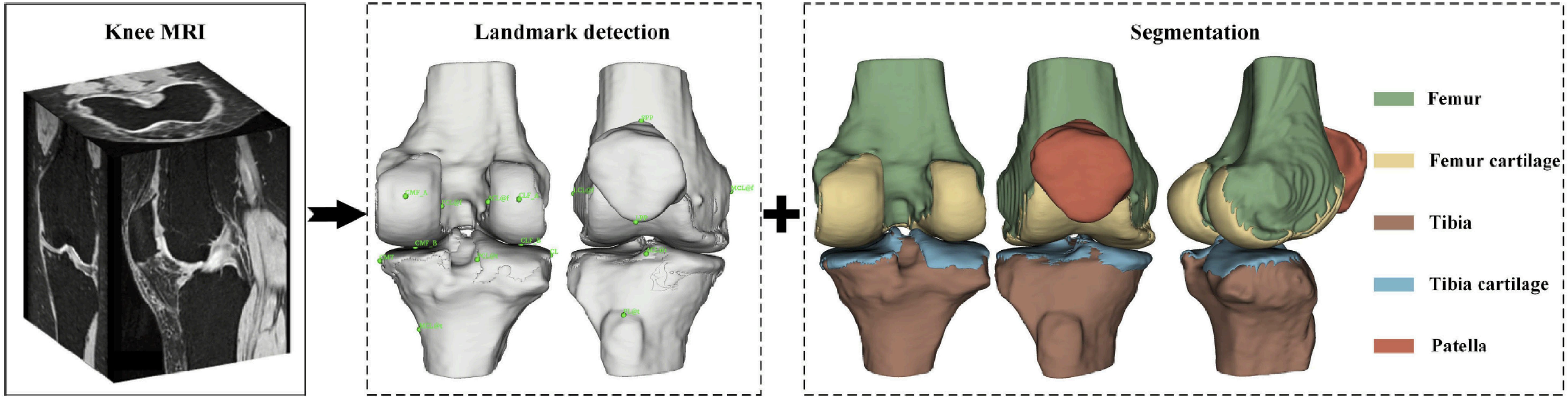


Detail of the three-branch network structure

SDMT

Spatial Dependence Multi-Task Transformer

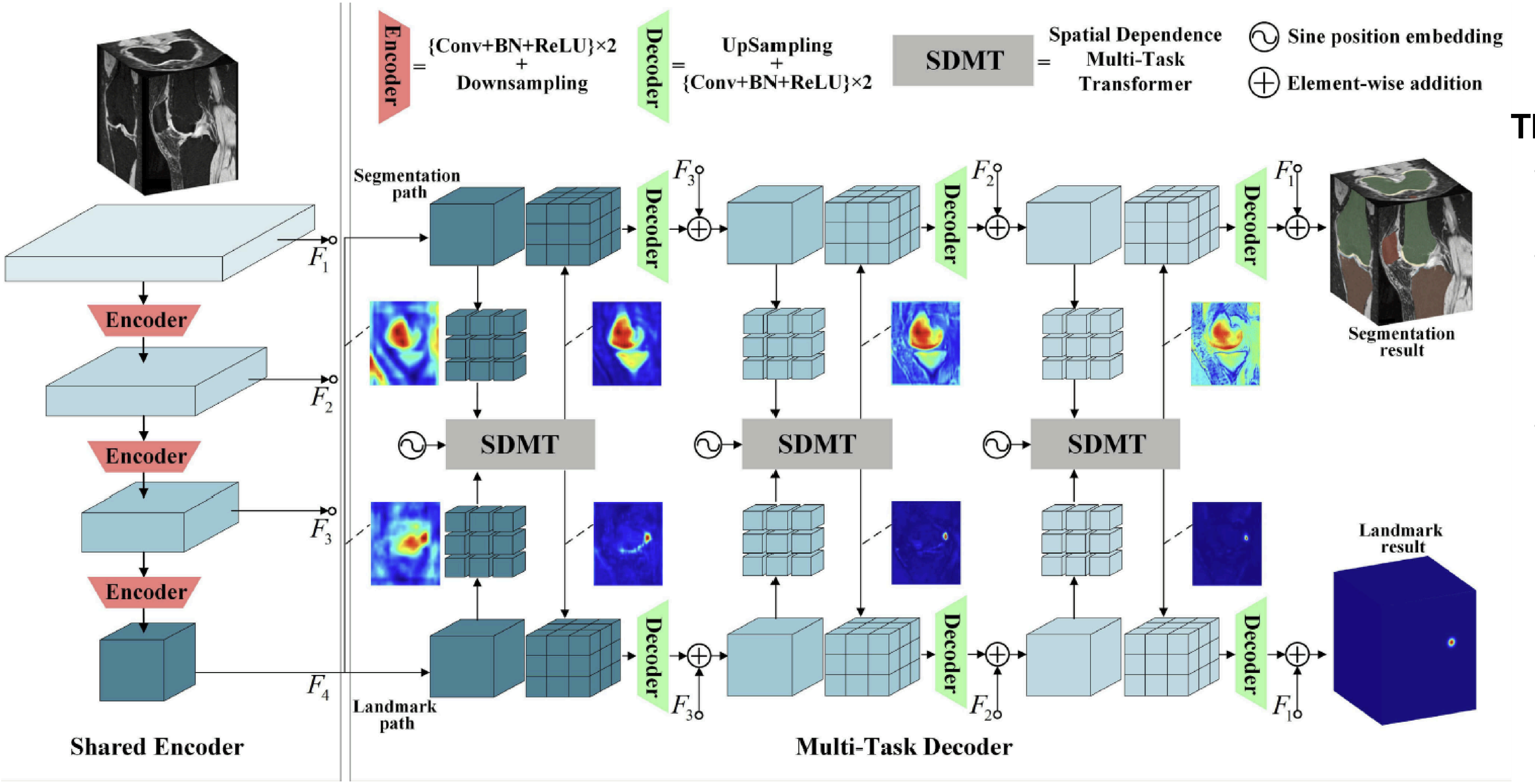
- **Tasks:** Joint 3D knee **MRI segmentation** + **landmark localization**
- **Architecture Innovations:**
  - Hybrid Multi-Head Attention:
    - **Inter-task attention:** Spatial dependence between tasks
    - **Intra-task attention:** Correlation within single task
  - Shared encoder for resource efficiency
  - **Dynamic weighted multi-mask loss**: Balanced optimization between tasks
- **Advantage:** Tasks mutually enhance each other through spatial dependencie**s**



The knee segmentation objectives and landmark localization objectives.

SDMT

Spatial Dependence Multi-Task Transformer



The overall network structure of the proposed method

Three-Stage Pipeline:

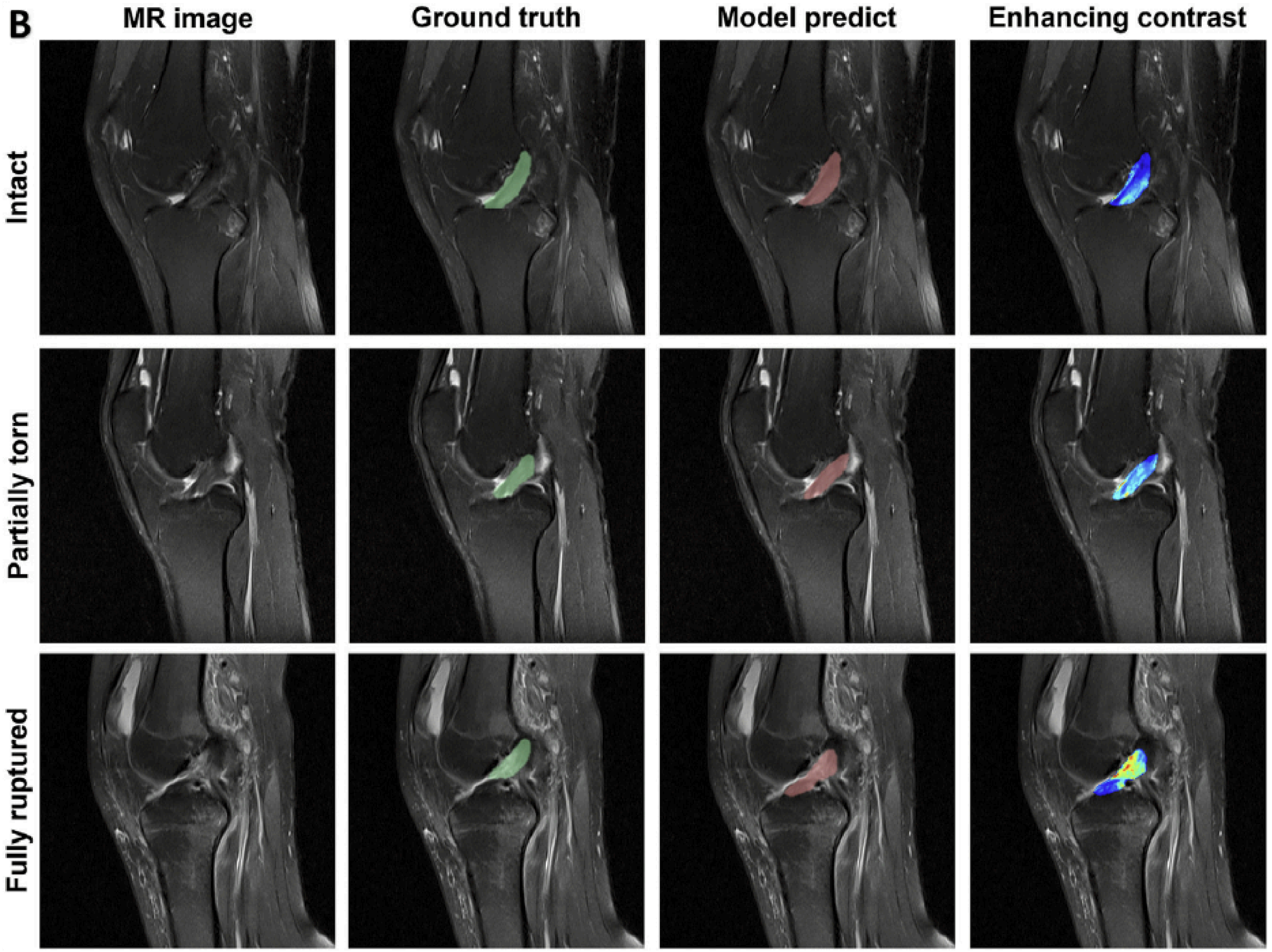
- **Shared Encoder** → Multi-scale feature extraction
- **SDMT Module** → Captures spatial dependencies + corrects features between tasks
- **Dual Decoders** → Independent segmentation and landmark outputs

DCLU-Net

Dual-Module System with Semi-Supervised Learning

Red/Yellow = High probability/confidence that this is ACL
Blue/Green = Lower probability
Shows the model's "certainty" across the region

- **Architecture:** Dual-module U-Net-based system
  - **Module 1:** Segmentation (3D-UNet based)
  - **Module 2:** Classification (Conv-3D + Linear layers)
- **Semi-Supervised Learning:**
  - Teacher model generates pseudo masks
  - Applied to 150 unlabeled samples
  - Reduces manual segmentation needs
- **Novel Feature:** Radiomic Features Integration
  - Extracted from segmented ACL masks
  - Backpropagated to classification module
  - Enhances classification ability
- **Advantage:** Leverages unlabeled data to improve performance

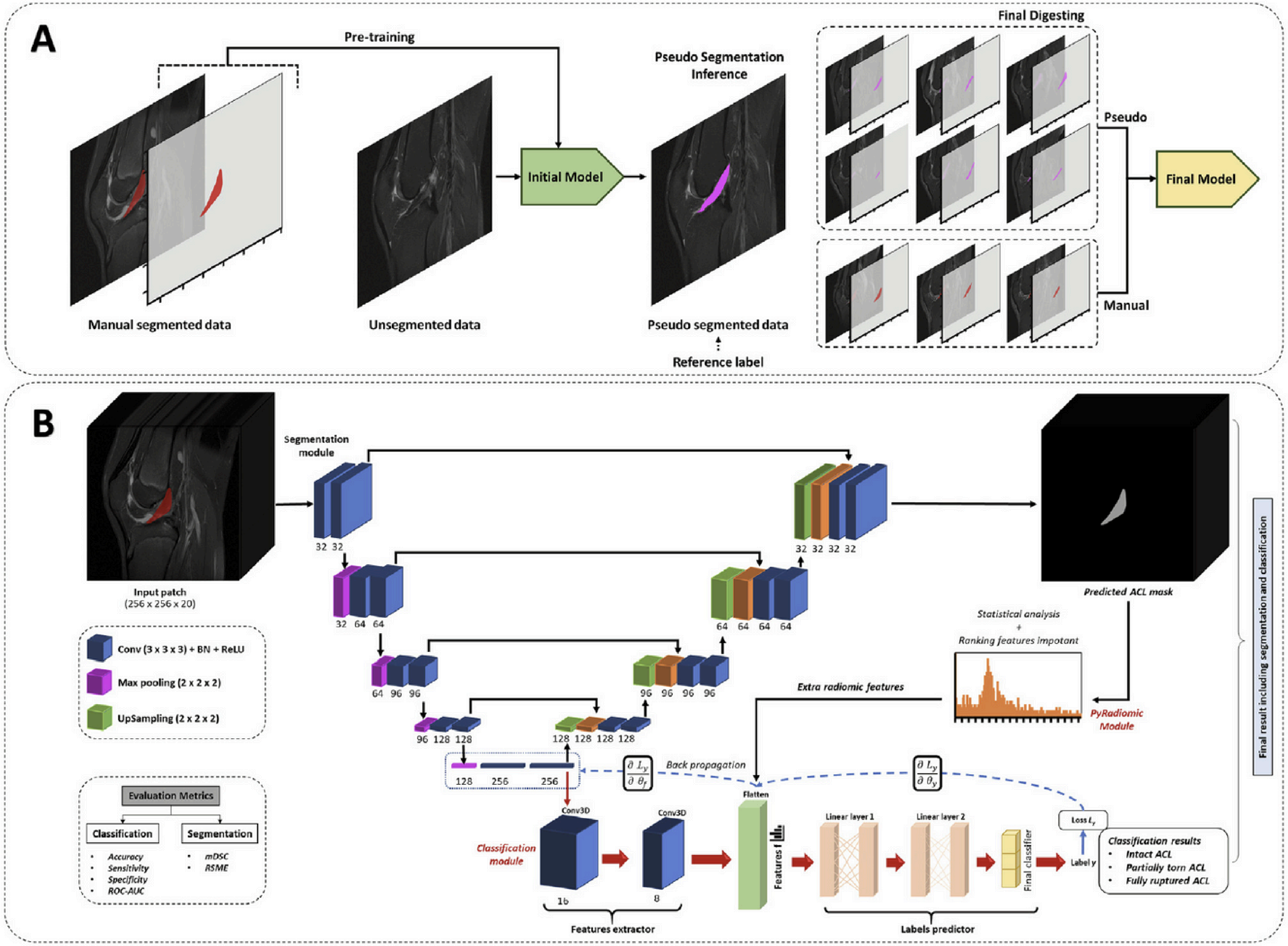


Illustrative examples of the model (with pseudo data) for segmentation of three classes and contrast-enhanced visualization of ACL region.

DCLU-Net

Dual-Module System with Semi-Supervised Learning

Overview of semi-supervised segmentation framework



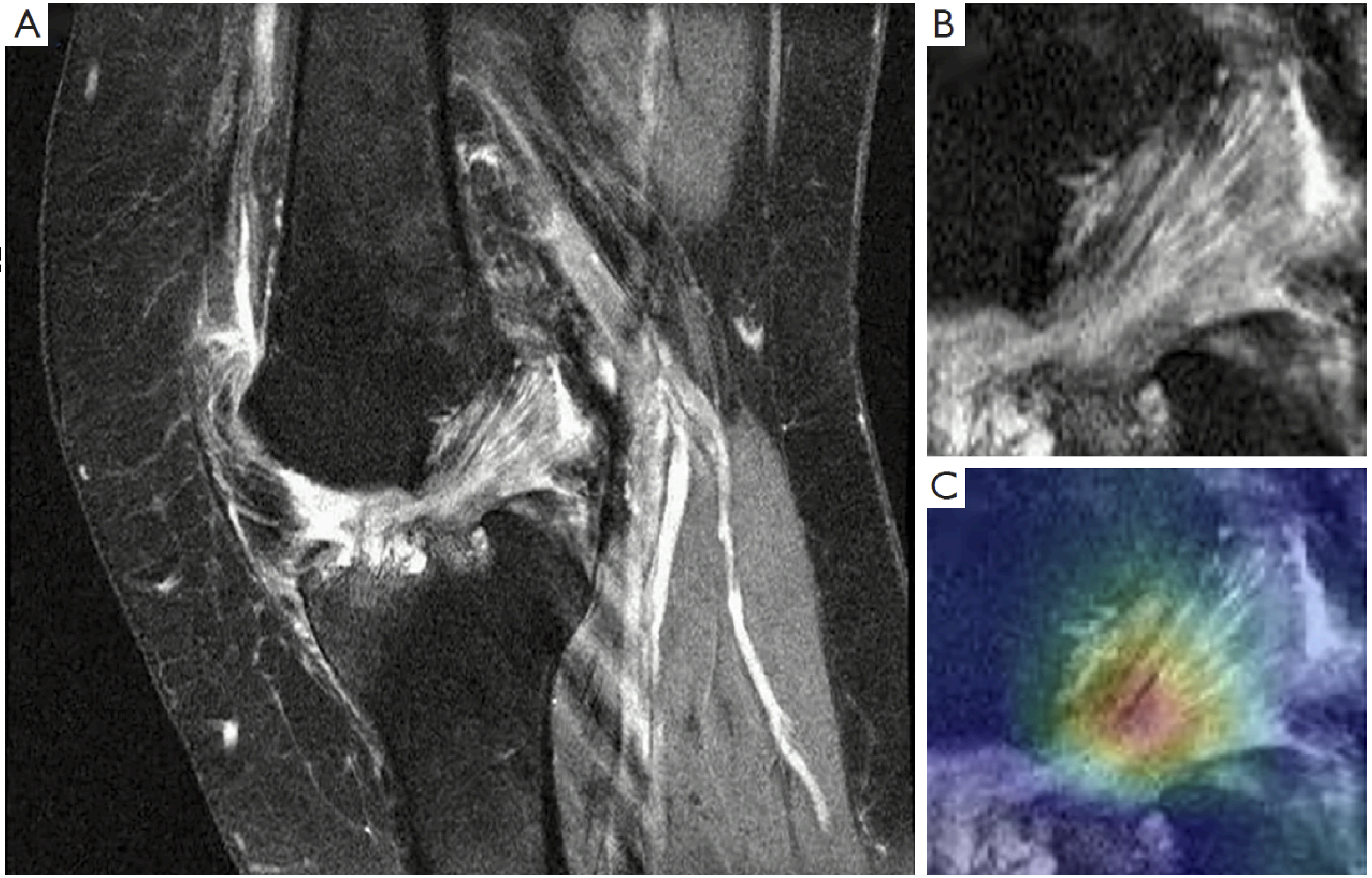
(A)DCLU-Net model with both segmentation & classification modules with extra radiomic features

(B)The segmentation: based on the 3D-UNet The classification module combined with two Conv-3D layers and two linear layers

One-Stop Detection

YOLOv5-Based Integrated System

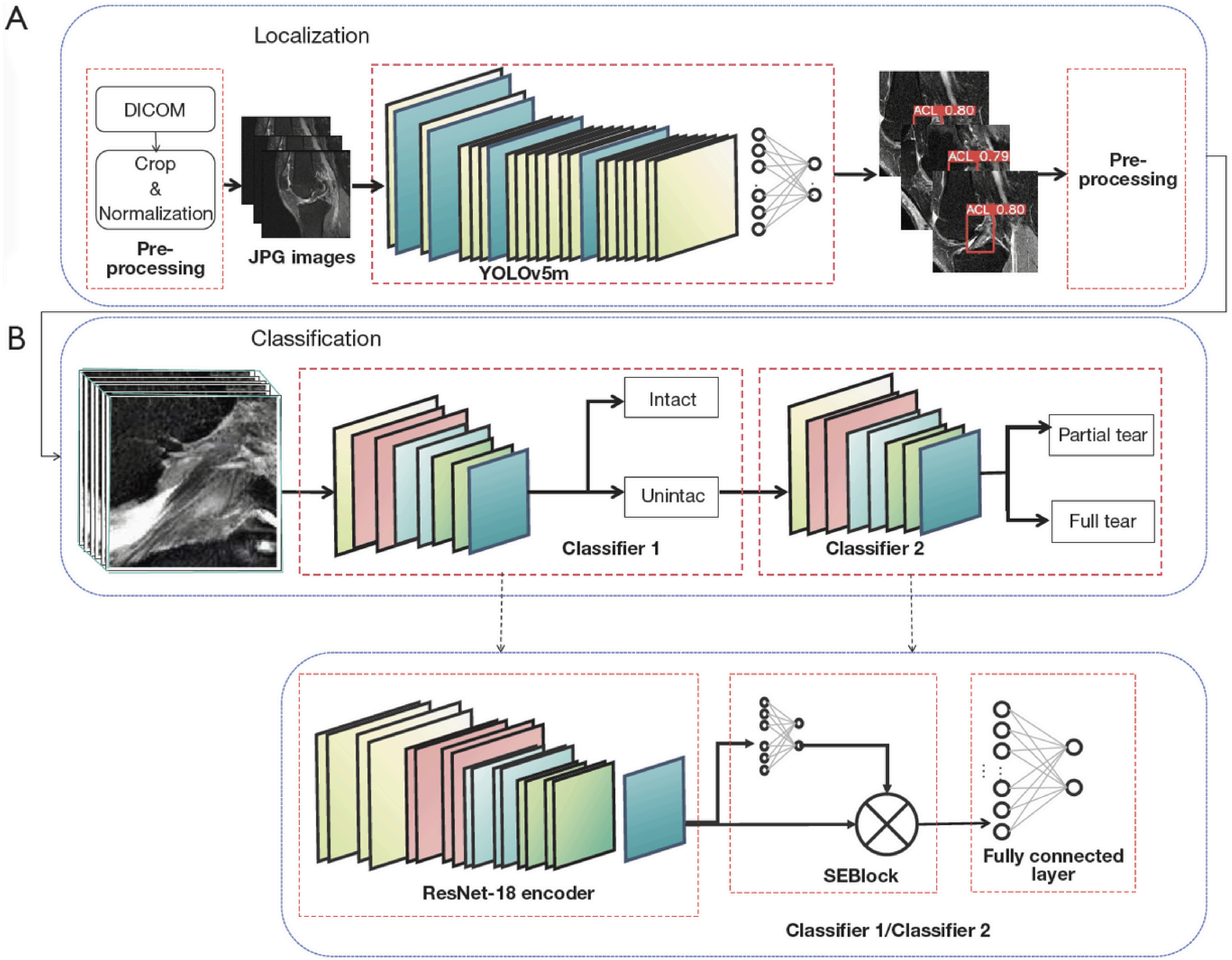
- **Two Main Components:**
  - **ACL Localization** (YOLOv5m)
  - **ACL Multi-Classification**:
    - S**queeze-and-Excitation (SE) blocks**
    - Integrates multi-slice data via attention weights
- **Outputs:**
  - ACL localization bounding box
  - Classification result
  - Probability plot for confidence visualization
- **Advantage:** 'One-stop' solution from localization to diagnosis



Sagittal MRI views of (A) a correctly classified knee with a partial tear ACL and (B) its ACL localization with, (C) probability plot

One-Stop Detection

YOLOv5-Based Integrated System



(A) ACL localization model

(B) ACL injury classification

Overview of the one-stop detection model pipeline

Conclusion

- **Major Achievements:**
  - **Segmentation**: 1-2 hours → <1 second per case
  - **Multi-class grading** approaching clinical standards
  - Few-shot learning enabling data-efficient deployment
  - Multi-plane models **mimicking radiologist workflow**
- **Clinical Integration Progress:**
  - Improved **interreader agreement** (Cohen's κ: 0.42 → 0.61)
  - **Real-time processing capabilities** (0.5s per scan)
  - Multi-task systems diagnosing 12+ abnormalities simultaneously

Thank you for your time and attention!