ACLNet: A Deep Learning Model for ACL Rupture Classification Combined with Bone Morphology

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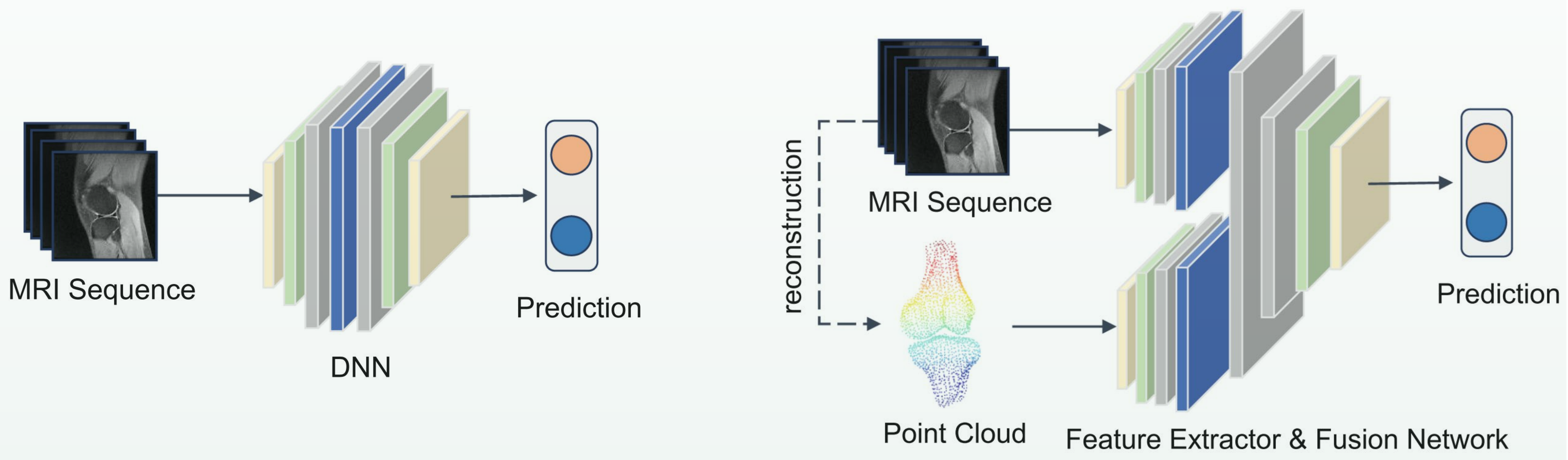
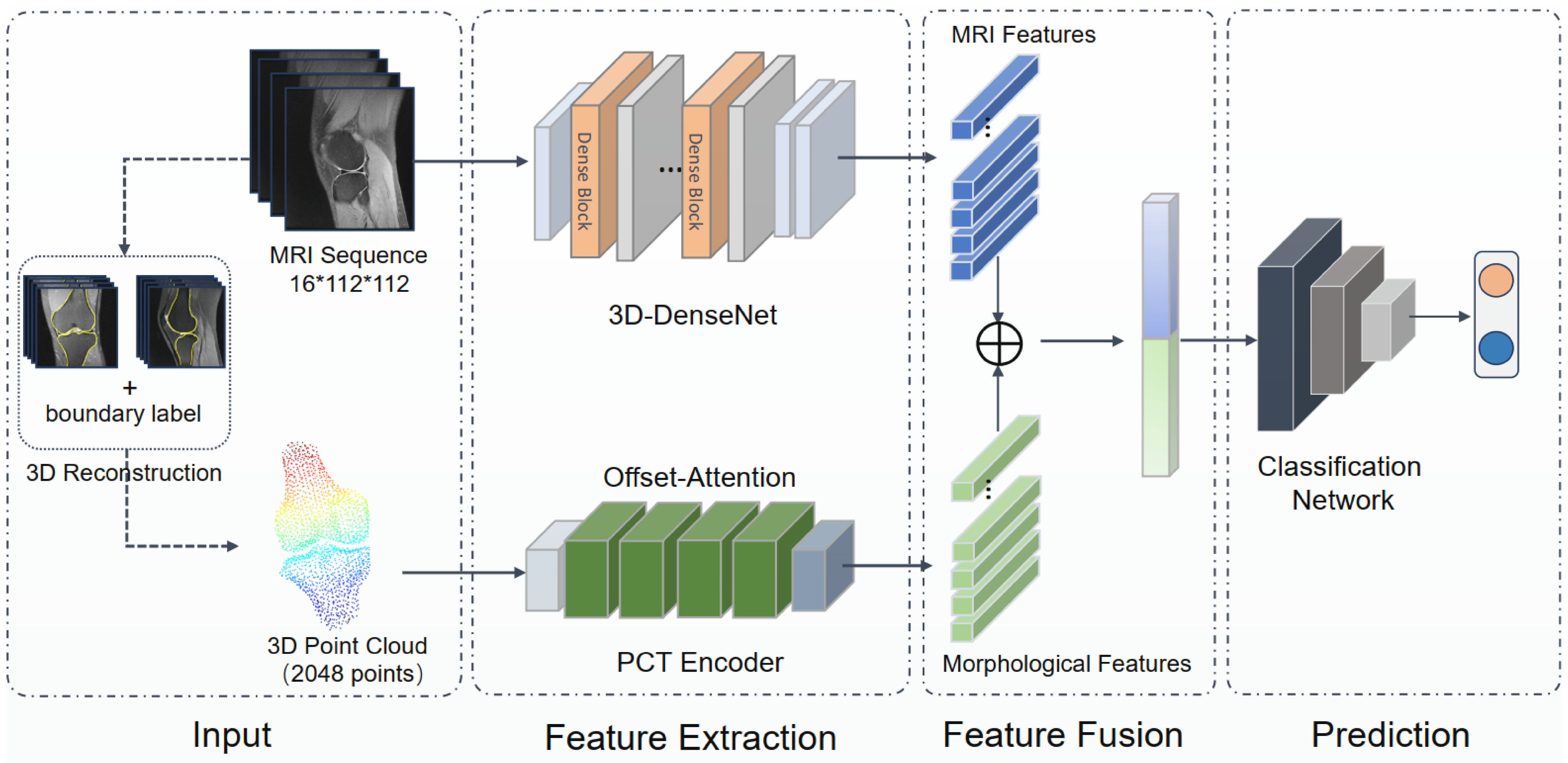
Motivation

- Prompt, accurate diagnosis of ACL(anterior cruciate ligament), followed by apt intervention is imperative to preserve knee joint functionality.
- Existing deep learning approaches often overlook additional factors beyond the image.
- Clinical observations have correlated certain femoral and tibial morphologies with increased ACL rupture risk[1, 2].
- We integrated bone morphological insights to feature extraction.



Previous Approach **ACLNet(Ours)**

Method



ACLNet's pipeline

☐ Baseline model

- After preprocessing MRI raw data, the corresponding three-dimensional image and point cloud representation data were obtained for each case.
- For the image branch, the input size was preprocessed to 16×112×112 pixel, we used densenet[3] as the feature extractor for its comprehensive feature integration ability.
- For the point cloud branch, each patient's input was uniformly preprocessed to 2048 points by farthest point sampling, and we chose PCT[4] as the feature extractor for its exceptionally adept at parsing the intricate structures of point clouds .

☐ Data flow

- Given an input, denoted as(X_i - image, P_i - point cloud):

$$\mathcal{D} = \{X_i, P_i\}(i = 1, 2 \ldots N)$$

- Extract feature of X_i and P_i by two branch F_{im} and F_{pc}, we get:

$$f_i^{im} = F_{im}(X_i), f_i^{pc} = F_{pc}(P_i)$$

- Blend the features of the two paths:

$$f_i = f_i^{im} \oplus f_i^{pc}$$

- Get the prediction by a classification layer:

$$\hat{y}_i = L(f_i)$$

- We adopted the cross-entropy loss function:

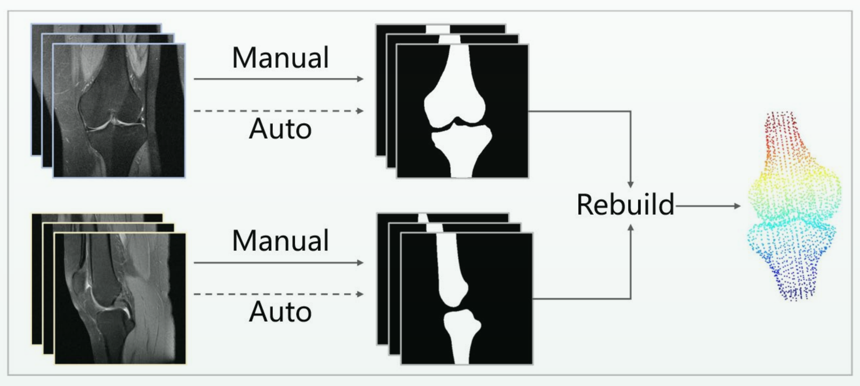
$$\mathcal{L}_{cls}(y_i, \hat{y}_i) = \frac{1}{N}\sum_{i=1}^{N}[y_i \ln(\hat{y}_i) + (1 - y_i)\ln(1 - \hat{y}_i)]$$

Dataset

Age	Female/male(%)	Rupture/normal(%)	Datasets	
			Train(%)	Validation(%)
31.8±11.2	670/1234(35.2/64.8)	947/957(49.7/50.3)	1521(79.9)	383(20.1)

Summary of Subject Demographic and Clinical Data

- 1904 MRI series, 54008 slices
- image — sagittal :
  - ✓ Organizational and structural details
- point cloud — sagittal & coronal :
  - ✓ Multidirectional morphological information



Flow chart for generating point clouds

Results

Method	$Acc\uparrow$	$Auc\uparrow$	$Prec\uparrow$	$Sens\uparrow$	$Spec\uparrow$	$F1\uparrow$
Reports by experts	**92.73**	-	**92.59**	**95.45**	90.53	**92.69**
MRNet	79.90	87.54	79.92	78.65	81.15	79.89
MRNet + PCT [4]	90.63	95.38	90.46	92.62	87.85	90.34
3D-DenseNet [3]	87.59	93.63	87.23	89.40	85.05	87.23
Ours	92.57	**96.57**	92.14	90.67	**95.28**	92.44

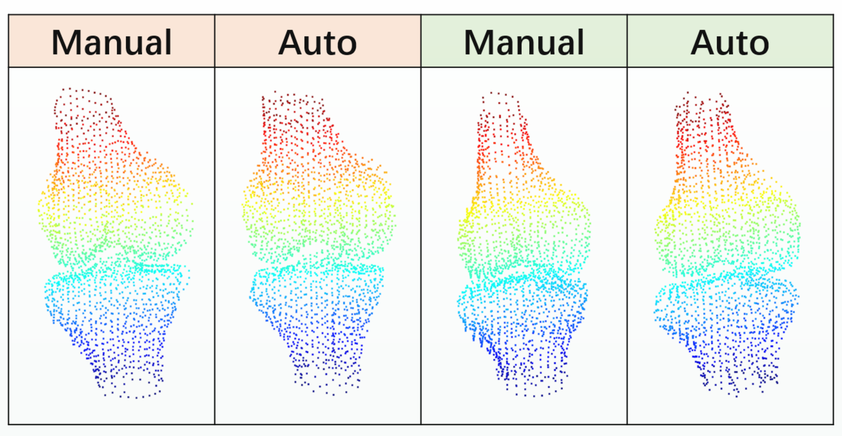
Comparation between methods

Method	Sample Points	Feature fusion	$Acc\uparrow$	$Auc\uparrow$	$Prec\uparrow$	$Sens\uparrow$	$Spec\uparrow$	$F1\uparrow$
3D-DenseNet [3]	-	-	87.59	93.63	87.23	89.40	85.05	87.23
PCT [4]	-	-	84.38	90.87	85.00	91.10	77.72	84.31
ACLNet	2048	$\otimes$	90.62	96.69	90.13	90.07	91.43	90.39
ACLNet	2048	$+$	90.62	**97.48**	90.20	91.17	94.34	90.48
ACLNet	2048	$\oplus$	**92.57**	96.57	**92.14**	90.67	**95.28**	**92.44**
ACLNet	1024	$\oplus$	88.20	92.12	85.83	88.67	86.79	86.98
ACLNet	4096	$\oplus$	89.84	94.77	90.03	**94.00**	83.96	89.41

Ablation of components $\oplus$: Concatenate, $+$: Weighted Sum, $\otimes$: Attention

Auto attempt

- To verify that this method still works for external data, we did an automated step by using the bone mask segmented by U2Net[5] rather than manual labeled boundary by expert In the point cloud generating part.



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MRNet + PCT [4]⋆	86.33	93.89	85.98	88.59	83.18	85.93
3D-DenseNet [3]	87.59	93.63	87.23	89.40	85.05	87.23
Ours	92.57	96.57	92.14	90.67	95.28	92.44
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⋆ for auto

References

[1] Al-Saeed, O., Brown, M., Athyal, R., Sheikh, M.: Association of femoral intercondylar notch morphology, width index and the risk of anterior cruciate ligament injury. Knee Surgery, Sports Traumatology, Arthroscopy **21**, 678–682 (2013)
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