Med-SeAM: Medical Context Aware Self-Supervised Learning Framework for Anomaly Classification in Knee MRI

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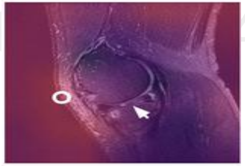
Introduction

The prevalence of meniscal tear is 12% to 14%, while the occurrence of ACL tear is 4% to 6% annually.

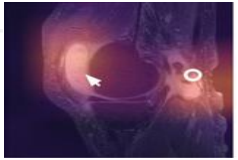
Challenges:

1. **Obtaining high-quality slice labels for diagnosing disorders from MRI volumes is challenging in medical settings.**
2. **Current self-supervised methods [3,13] rely on simplistic label assignments for pretext tasks.**
3. **Medical imaging poses challenges for deep learning due to grayscale nature, non-differential spatial context, and small ROIs relative to image dimensions.**

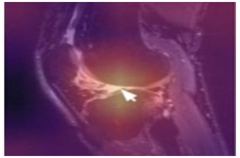
Complete anterior cruciate ligament (ACL) tear (arrow)



Meniscal tear at posterior horn of the lateral meniscus (arrow)



Abnormality: Large effusion (arrow)



Complete ACL Tear (arrow), abnormal attachment of ACL

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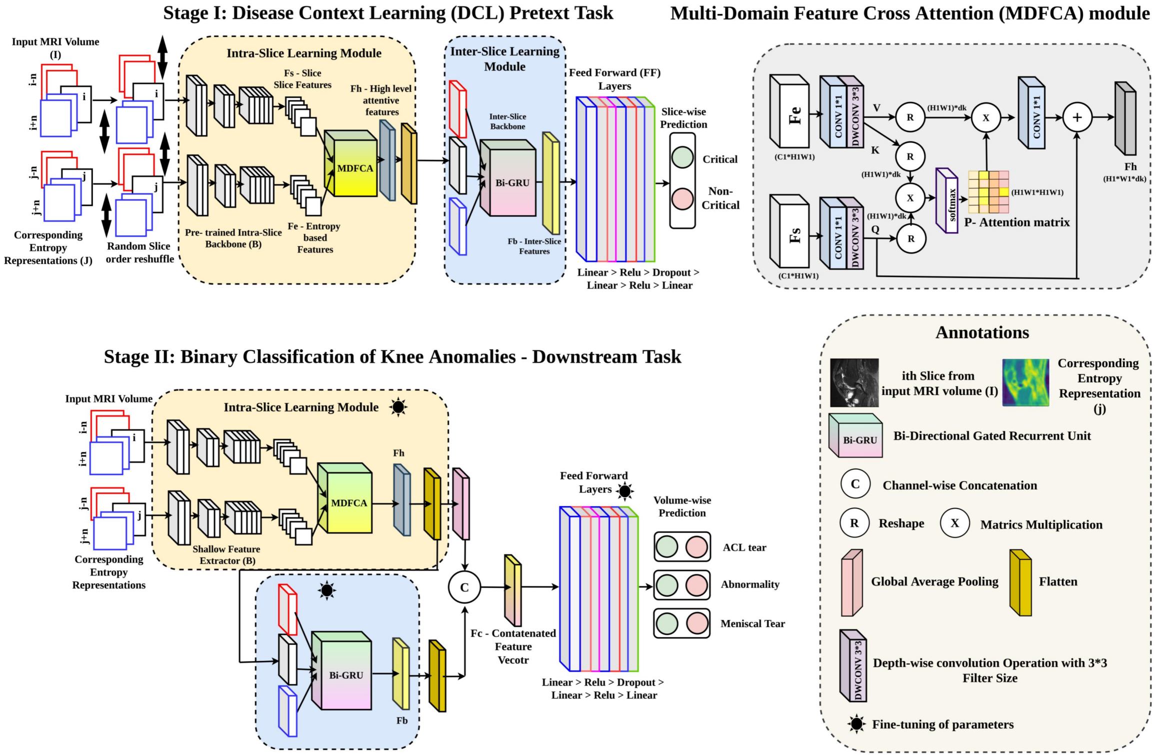
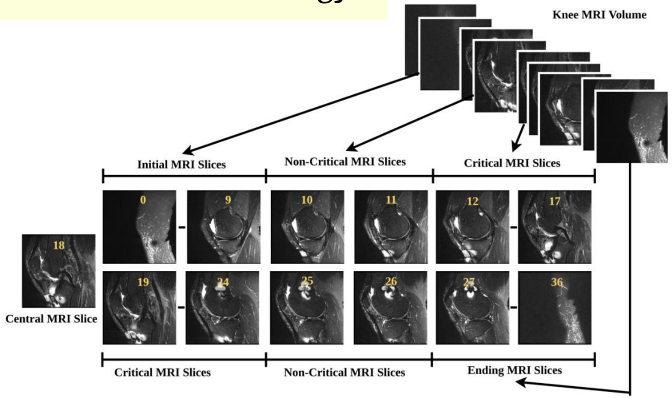
Proposed Scheme

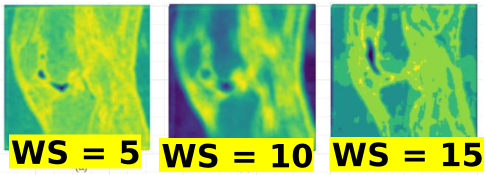
Figure 1: Schematic of proposed Med-SeAM framework



Slice Selection Strategy



Entropy Maps



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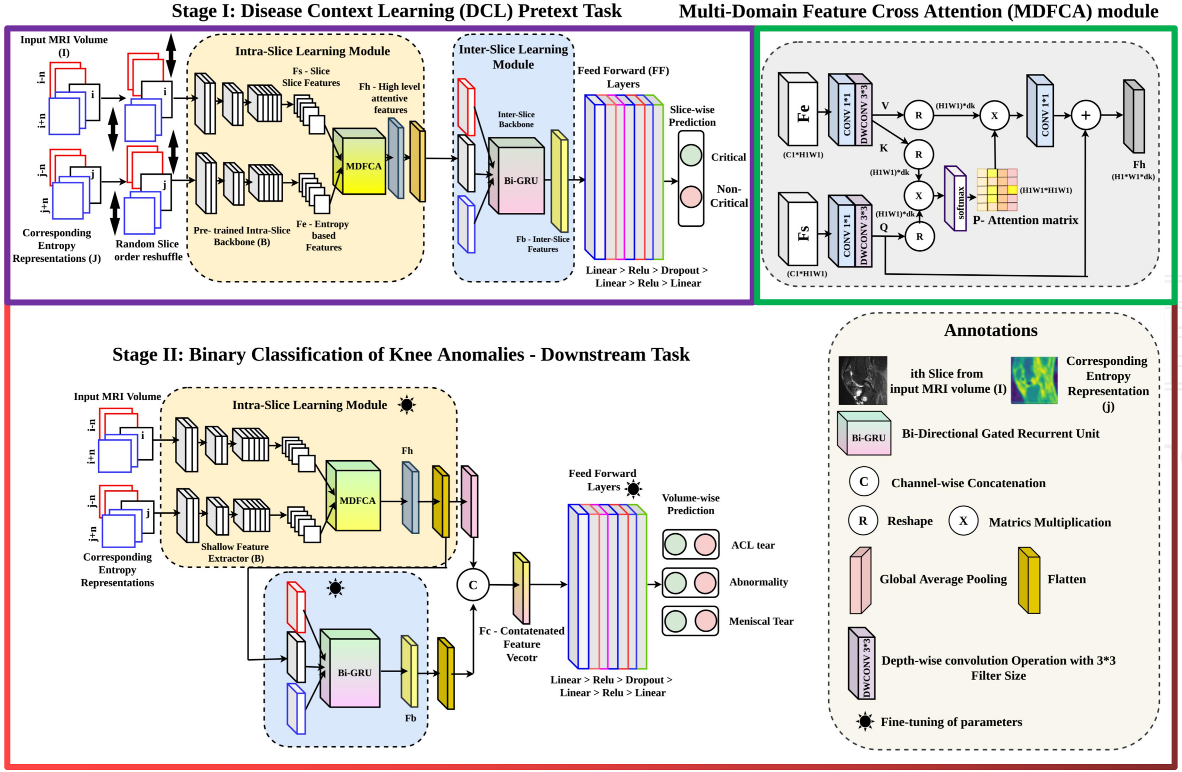


Contributions:

(1) A novel two-step self-supervised scheme, **Med-SeAM** for **binary classification** from MRI volumes of the knee.
Anomalies : Abnormality, meniscal tear and ACL tear

(2) A novel pretext task, **Disease Context Learning (DCL)**, is proposed to predict the critical MRI slices in MRI volume.

(3) A **Multi-Domain Cross Attention (MDFCA) module** is proposed to contemplate the cross attention between the MRI slices and its entropy counterpart.

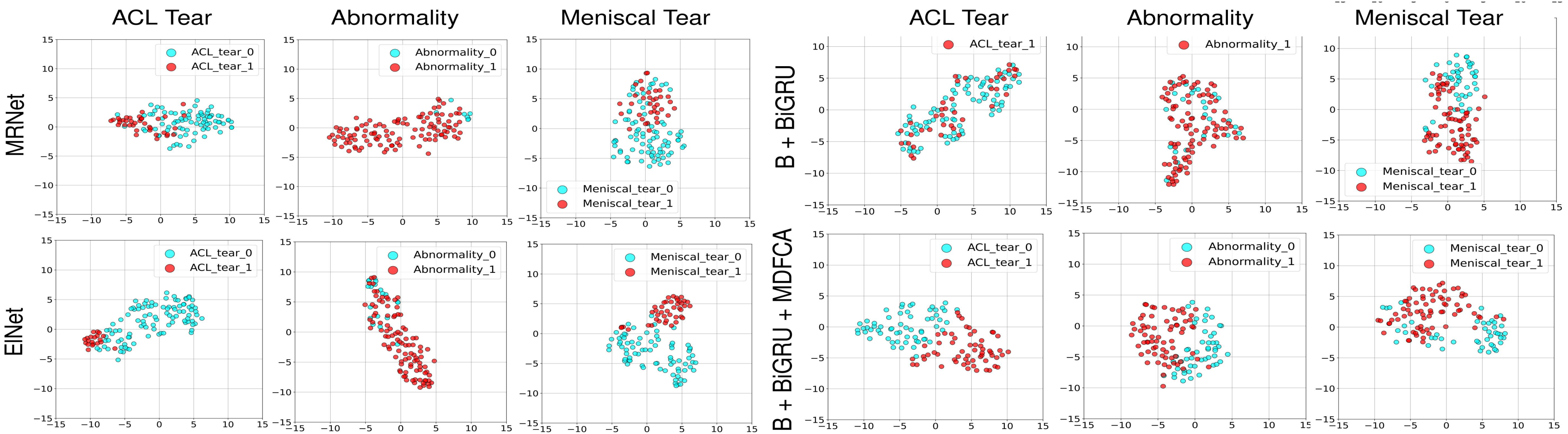
Experimental Results

Table 1: Comparison of the proposed Med-SeAM framework with SOTA

Type	Architecture	Accuracy	Sensitivity/Specificity	AUC
ACL tear	MRNet [1]	**0.791**	**0.703** / 0.863	**0.872**
Abnormality		**0.858**	**0.957** / 0.486	**0.921**
Meniscus Tear		0.683	0.615 / **0.750**	0.740
ACL tear	EINet [2]	0.750	0.500 / **0.954**	0.807
Abnormality		0.783	0.949 / 0.660	0.802
Meniscus Tear		**0.700**	0.712 / 0.576	0.716
ACL tear	SKID [3]	0.691	0.111 / **0.988**	0.825
Abnormality		0.825	**0.979** / 0.240	**0.883**
Meniscus Tear		0.675	0.753 / 0.471	**0.760**
ACL tear	Proposed Model (w/o SSL)	0.692	0.674 / 0.760	0.717
Abnormality		0.810	0.890 / **0.687**	0.816
Meniscus Tear		0.642	**0.766** / 0.587	**0.753**
ACL tear	Proposed Model	**0.767**	**0.776** / 0.704	**0.837**
Abnormality		**0.875**	0.926 / **0.683**	0.803
Meniscus Tear		**0.742**	**0.760 / 0.680**	0.719

Experimental Results

Figure 2: Comparison of the proposed Med-SeAM framework with SOTA using tSNE plots



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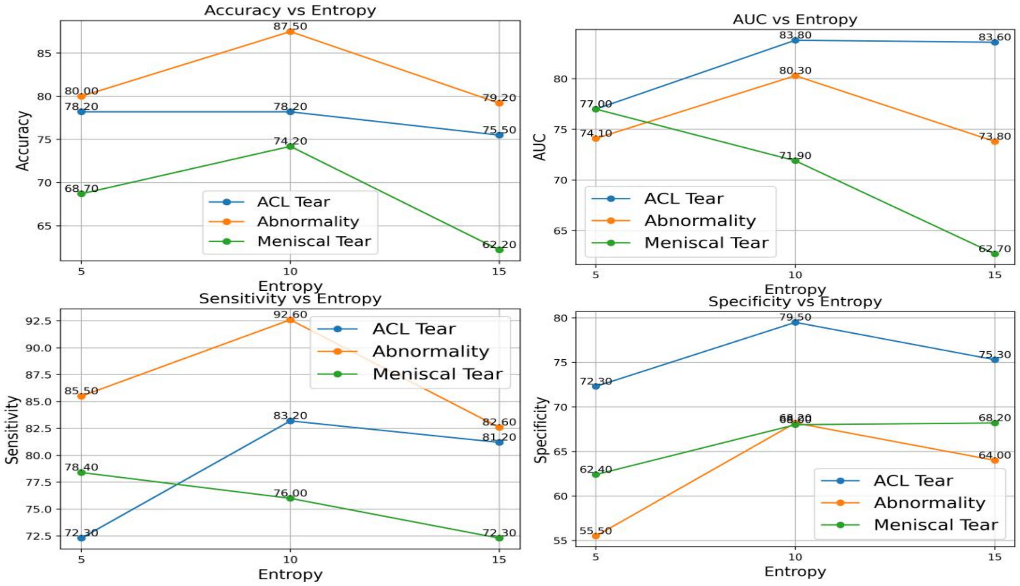
Ablation Study

Table 2: Effect of proposed DCL Pretext Task

Architecture	ACL Tear	Abnormality	Meniscal Tear
SimCLR [11]	0.618 / 0.688	0.722 / 0.649	0.603 / 0.654
MoCoV2 [12]	0.449 / 0.390	0.727 / 0.690	0.547 / 0.610
SKID [3]	0.691 / 0.825	0.825 / **0.883**	0.641 / **0.760**
Context-aware SSL [13]	**0.751**/ **0.913**	**0.855** / **0.855**	**0.671**/ **0.788**
Proposed Model	**0.767**/ **0.837**	**0.875** / 0.803	**0.742**/ 0.719

Figure 3: Effect of Entropy window sizes



Ablation Study

Table 3: Effect of proposed MDFCA for different intra-slice and inter-slice backbones

Architectures ↓	ACL Tear (Accuracy / AUC)	ACL ear (Sensitivity / Specificity)	Abnormality (Accuracy / AUC)	Abnormality (Sensitivity / Specificity)	Meniscal Tear (Accuracy / AUC)	Meniscal Tear (Sensitivity / Specificity)
Alexnet [4] + LSTM [5]	0.733 / 0.729	0.658 / 0.772	0.780 / 0.741	0.812 / 0.621	0.658 / 0.673	0.788 / 0.558
Alexnet [4] + Bi-GRU [6]	0.691 / 0.691	0.685 / 0.697	0.810 / 0.791	0.840 / 0.640	0.634 / 0.690	0.787 / 0.573
Alexnet [4] + MDFCA + LSTM [5]	0.741 / 0.718	0.698 / 0.752	0.800 / 0.811	0.842 / 0.680	0.652 / 0.713	0.766 / 0.587
Alexnet [4] + MDFCA + Bi-GRU [6]	0.722 / 0.791	0.735 / 0.745	0.850 / 0.812	0.844 / 0.720	0.742 / 0.719	0.760 / 0.680
VGG-19 [7] + LSTM [5]	0.725 / 0.723	0.703 / 0.747	0.824 / 0.686	0.891 / 0.440	0.608 / 0.631	0.807 / 0.459
VGG-19 [7] + Bi-GRU [6]	0.775 / 0.773	0.759 / 0.787	0.833 / 0.732	0.905 / 0.660	0.633 / 0.663	0.884 / 0.441
VGG-19 [7] + MDFCA + LSTM [5]	0.715 / 0.718	0.698 / 0.752	0.833 / 0.732	0.905 / 0.660	0.618 / 0.616	0.822 / 0.439
VGG-19 [7] + MDFCA + Bi-GRU [6]	0.785 / 0.793	0.780 / 0.822	0.840 / 0.792	0.844 / 0.720	0.629 / 0.667	0.900/ 0.449
Resnet-50 [8] + LSTM [5]	0.667 / 0.627	0.694 / 0.560	0.675 / 0.662	0.684 / 0.640	0.567 / 0.572	0.615 / 0.529
Resnet-50 [8] + Bi-GRU [6]	0.591 / 0.601	0.703 / 0.500	0.658 / 0.651	0.663 / 0.640	0.583 / 0.575	0.519 / 0.632
Resnet-50 [8] + MDFCA + LSTM [5]	0.665 / 0.647	0.728 / 0.596	0.699 / 0.683	0.701 / 0.650	0.587 / 0.602	0.622 / 0.549
Resnet-50 [8] + MDFCA + Bi-GRU [6]	0.589 / 0.605	0.707 / 0.504	0.688 / 0.705	0.691 / 0.671	0.608 / 0.605	0.499 / 0.657
Densenet-121 [9] + LSTM [5]	0.697 / 0.766	0.746 / 0.793	0.826 / 0.783	0.874 / 0.640	0.641 / 0.625	0.500 / 0.750
Densenet-121 [9] + Bi-GRU [6]	0.733 / 0.737	0.778 / 0.697	0.780 / 0.741	0.734 / 0.642	0.558 / 0.599	0.908/ 0.293
Densenet-121 [9] + MDFCA + LSTM [5]	0.699 / 0.768	0.744 / 0.791	0.866/ 0.813	0.925/ 0.680	0.636 / 0.628	0.496 / 0.745
Densenet-121 [9] + MDFCA + Bi-GRU [6]	0.741 / 0.732	0.782 / 0.702	0.897 / 0.607	0.846 / 0.691	0.897 / 0.609	0.687 / 0.621
Mobilenet-V2 [10] + LSTM [5]	0.722 / 0.767	0.702 / 0.743	0.828 / 0.698	0.875 / 0.621	0.600 / 0.574	0.384 / 0.746
Mobilenet-V2 [10] + Bi-GRU [6]	0.767 /0.833	0.833/ 0.790	0.826 / 0.783	0.862 / 0.610	0.633 / 0.574	0.384 / 0.764
Mobilenet-V2 [10] + MDFCA + LSTM [5]	0.730 / 0.772	0.707 / 0.738	0.858 / 0.778	0.915 / 0.671	0.618 / 0.593	0.375 / 0.802
Mobilenet-V2 [10] + MDFCA + Bi-GRU [6]	0.782/ 0.838	0.832 / 0.795	0.875/ 0.803	0.926 / 0.682	0.645 / 0.624	0.334 / 0.792

Conclusion

1. The Med-SeAM framework is found to improve classification performance of abnormality by 10.61% in accuracy and 3.5% in sensitivity, while for meniscal tear, the improvement is about 2.06% in accuracy compared to SOTA.

2. The Med-SeAM outperforms Context-Aware SSL [13] by 2.13% in average accuracy for detecting knee anomalies. This significant improvement stems from integrating domain knowledge, leveraging the spatial consistency and minimal dynamic changes in medical images.

3. The proposed DCL pretext task can be effectively applied to volume-based data, even in the absence of explicit slice labels.

Selected References

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Thank You !!

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