Integrating Medical Knowledge into Deep Learning Architectures

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Our Team



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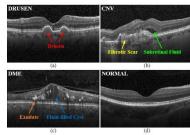
The Need of Deep Learning in Medical Imaging

Practical perspective: To help the clinicians for dependable medical assistance.

Research perspective: Medical images involves visual and latent information of disease biomarkers that can be traced using deep learning.

Tasks: Disease diagnosis, Lesion, organ, and abnormality detection, Lesion, organ segmentation, medical image registration, medical image retrieval, Medical report generation.

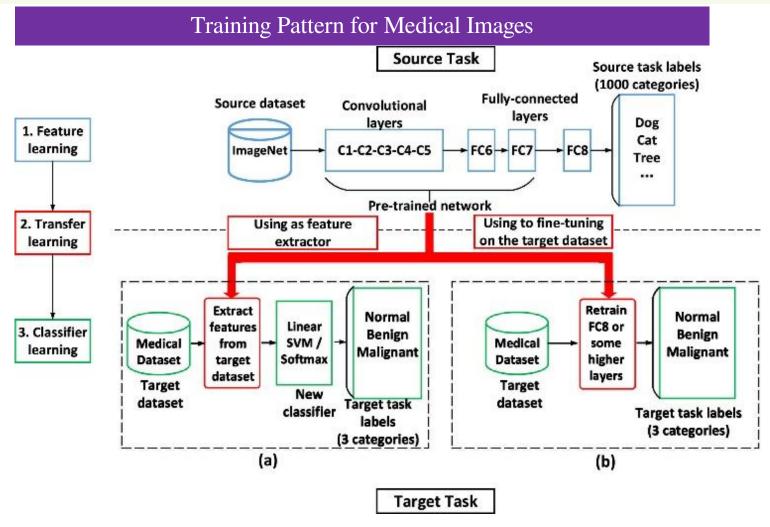
Challenges: Medical images are grayscale in nature, have non-differential spatial context and often contains small ROI compared to image dimensions.





OCT image

MRI



- 1. The training pattern
- 2. The general diagnostic patterns they view images- MRI, CT
- 3. The areas on which they usually focus-knee xray
- 4. The features (e.g characteristics, structures, shapes) they give special attention to, and Cancer
- 5. Other related information for diagnosis

Two strategies to utilize the pre-trained network on natural images: (a) as a feature extractor and (b) as an initialization which will be fine-tuned on the target dataset [Xie et al.].

Incorporating domain knowledge to Classification

1. Training Deep learning model with disease specific descriptors

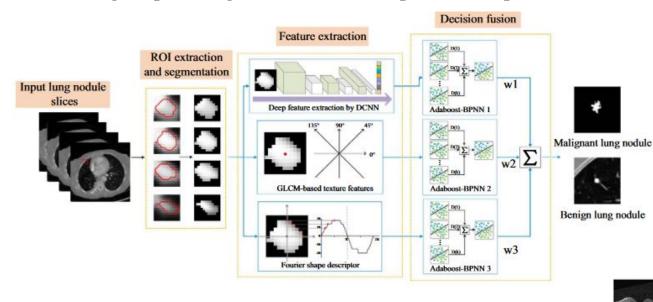
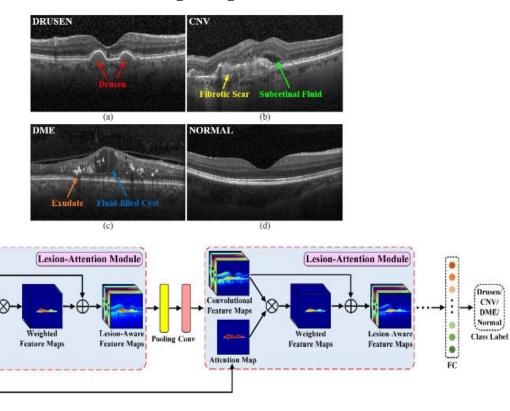


Diagram of Fuse-TSD lung nodule classification algorithm.

Texture and shape descriptors such as gray level co-occurance matrix, faret shape measure, moment invariants, point distance histograms and fourier descriptors can be used to characterize heterogeneous shape of the nodules [Xie et al.]

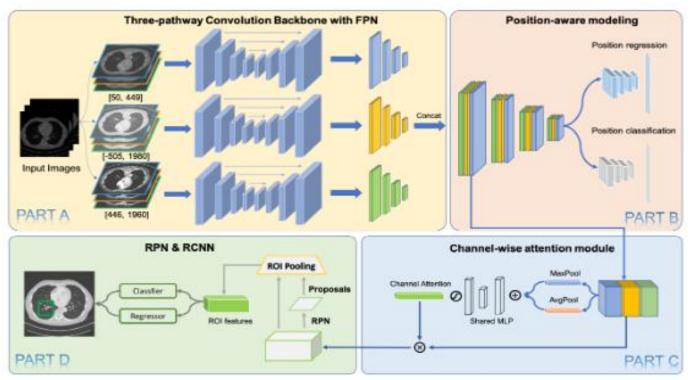
2. Utilizing Attention Mechanism for guiding the classification tasks



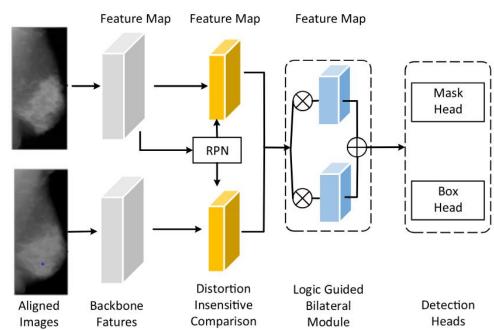
The framework of LACNN for retinal OCT image classification [Fang et al.]

Incorporating domain knowledge to Object Detection

3. Utilizing images under different settings/Multiple views/modalities/analyzing adjacent slides for computer vision tasks



Overview of MVP-Net. Coarser feature maps of FPN are omitted in part C and D for clarity, they use the same attention module with shared parameters for feature aggregation [Li et al.]



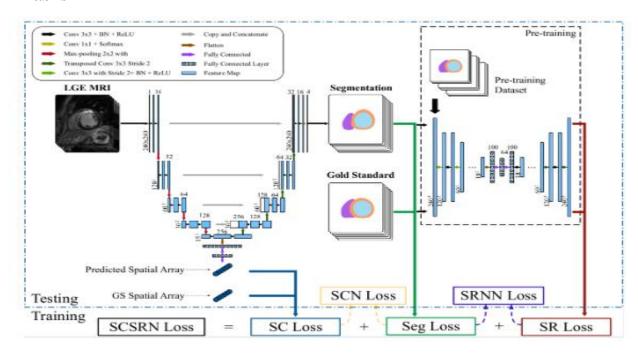
The workflow of mammogram mass detection by integrating the bilateral information (Liu et al., 2019), where the aligned images are fed into two networks seperately to extract features for further detection [Liu et al.]

Li, Zihao, et al. "MVP-Net: multi-view FPN with position-aware attention for deep universal lesion detection." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2019.

Liu, Yuhang, et al. "From unilateral to bilateral learning: Detecting mammogram masses with contrasted bilateral network." *Medical Image Computing and Computer Assisted Intervention-MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part VI 22.* Springer International Publishing, 2019.

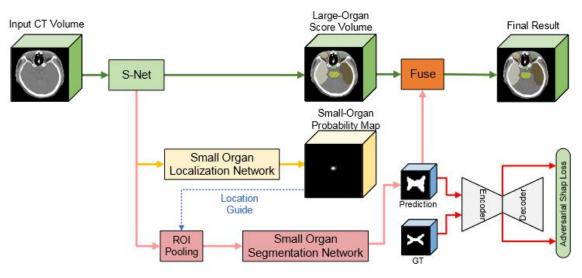
Incorporating domain knowledge to Segmentation

4. Utilizing loss function as regularizing term for fine tuning the Segmentation masks



Overall structure of SRSCN, whose loss comes from three parts: the segmentation loss is specially design as a function of cross entropy and Dice, the spatial constraint (SC) loss to assist segmentation, and the shape reconstruction (SR) loss for shape regularization [Yue et al.]

5. Utilizing localization network to locate small tissues for fine tuning the segmentation results



Overall framework - FocusNetv2 [Gao et al.]

Our Approach

Currently our team is focused on: Disease diagnosis, Lesion, organ, and abnormality detection, Lesion, organ segmentation, and Medical report generation.

Our research Team currently working on:

- Classification of Knee Osteoarthritis using Gait Data.
- Medical report generation of chest X-ray using vision-language model.

Past works and Publications:

- Jain, Rohit Kumar, et al. "Knee osteoarthritis severity prediction using an attentive multi-scale deep convolutional neural network." *Multimedia Tools and Applications* 83.3 (2024): 6925-6942.
- Daydar, Akshay, et al. "Segmentation of Multiple Knee Tissues from MR images using MtRA-Unet and Incorporating Shape Information: Data from Osteoarthritis Initiative" [Under Review at Medical & Biological Engineering & Computing]

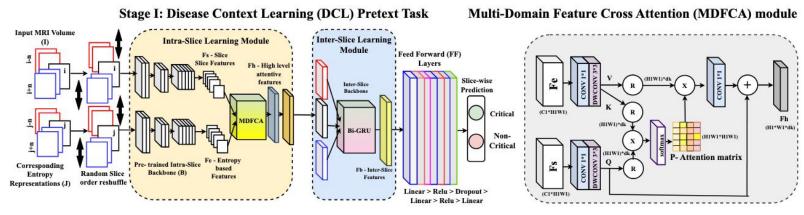
Our Approach

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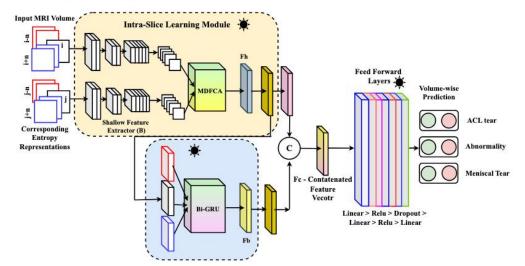
- Daydar, Akshay, et al. "Med-SeAM: Medical Context Aware Self-Supervised Learning Framework for Anomaly Classification in Knee MRI." *Proceedings of the Fifteenth Indian Conference on Computer Vision Graphics and Image Processing*. 2024.
- Daydar, Akshay, et al. "MedCAM-OsteoCls: Medical Context Aware Multimodal Classification of Knee Osteoarthritis", *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)* 2025.
- Daydar, Akshay, et al. "DeepOsteoCls:Deep Learning-Based Framework for Knee Osteoarthritis Classification With Qualitative Explanations from Radiographs and MRI Volumes", [Under Review at *Biomedical Signal Processing and Control*].

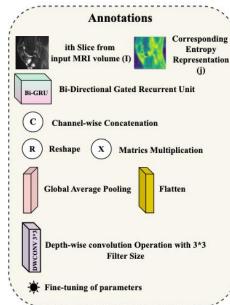
Med-SeAM Framework

Med-SeAM: Medical Context Aware Self-Supervised Learning Framework for Anomaly Classification in Knee MRI [Daydar et al.]



Stage II: Binary Classification of Knee Anomalies - Downstream Task





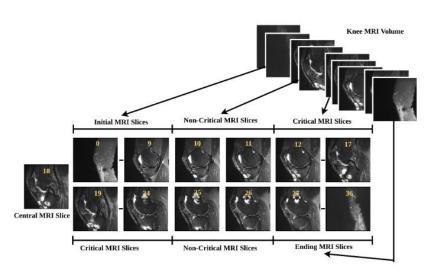


Figure: Schematic of the slice selection strategy.

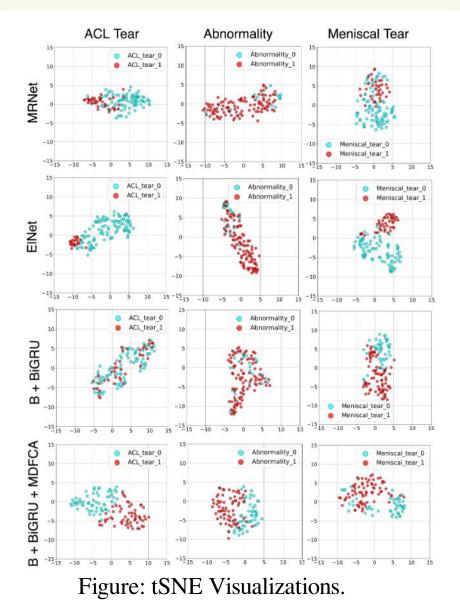
Daydar, Akshay, et al. "Med-SeAM: Medical Context Aware Self-Supervised Learning Framework for Anomaly Classification in Knee MRI." *Proceedings of the Fifteenth Indian Conference on Computer Vision Graphics and Image Processing*. 2024.

Figure: Schematic of the proposed Med-SeAM framework.

Results

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

Type	Architecture	Accuracy	Sensitivity /Specificity	AUC
ACL tear		0.791	0.703/0.863	0.872
Abnormality	MRNet [1]	0.858	0.957/0.486	0.921
Meniscus Tear	\$ 520	0.683	0.615/0.750	0.740
ACL tear		0.750	0.500/0.954	0.807
Abnormality	ElNet [30]	0.783	0.949/0.660	0.802
Meniscus Tear	#2 1 F	0.700	0.712/0.576	0.716
ACL tear		0.691	0.111/0.988	0.825
Abnormality	SKID[19]	0.825	0.979/0.240	0.883
Meniscus Tear		0.675	0.753/0.471	0.760
ACL tear	Proposed	0.692	0.674/0.760	0.717
Abnormality	Model	0.810	0.890/ 0.687	0.816
Meniscus Tear	(w/o SSL)	0.642	0.766/0.587	0.753
ACL tear	Proposed	0.767	0.776/0.704	0.837
Abnormality	Model	0.875	0.926/0.683	0.803
Meniscus Tear		0.742	0.760/0.680	0.719





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Research Areas: Medical Imaging, Deep Learning, Biomechanics



https://adaydar.github.io/

