

CAP-5516 Medical Image Computing (Spring 2025)

Project Ideas/Topics

Dr. Chen Chen

Note: The project must be medical image analysis using deep learning methods.

Some project ideas can be found from the following resources:

<https://grand-challenge.org/>

MICCAI workshops and challenges:

<https://conferences.miccai.org/2023/en/challenges.asp>

<https://conferences.miccai.org/2023/en/workshops.asp>

<https://conferences.miccai.org/2024/en/challenges.asp>

<https://conferences.miccai.org/2024/en/workshops.asp>

<https://www.kaggle.com/competitions?tagIds=4202-Healthcare>

<https://www.kaggle.com/search?q=medical+image+in%3Adatasets>


[Grand Challenge](#) [Challenges](#) [Algorithms](#) [Reader Studies](#) [...](#)

[Help](#) [Sign In](#) [Register](#)

[+ Host your own Challenge](#)

[Filter Challenges](#) [X Remove Filters](#)

Filters included 8 of 180 total challenges




BCI
Breast Cancer
Immunohistochemical Image
Generation Challenge

Breast Cancer Immuno...

Accepting submissions for Post Challenge Phase

802 18 2022

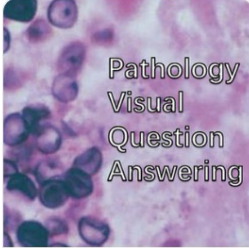


TIGER

Algorithm submission challenge

Accepting submissions for Segmentation and Detection (Experimental)

1,309 398 2021




Pathology
Visual
Question
Answering

Pathology Visual Questi...

Not accepting submissions

65 2020

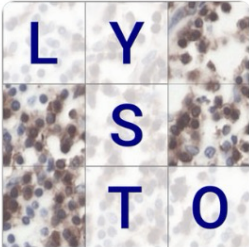


PAIP2020
MSI Prediction in Colorectal Cancer

PAIP2020

Accepting submissions for Validation

830 679 2020




LYSTO

Lymphocyte Assessmen...

Accepting submissions for Challenge

771 422

COMPAY 2019 2019

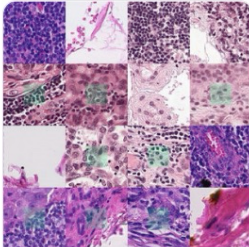


GLEASON2019

Gleason2019

Not accepting submissions


313 2019



PatchCamelyon

Accepting submissions for Challenge

495 179 2019



ACDC
LungHP

ACDC-LungHP

Accepting submissions for Challenge

663 26

ISBI 2019 2019

Example Projects:

1. Diffusion models for medical image analysis (e.g., image generation, segmentation, etc.)

Other related topics:

- Diffusion model for super resolution, data generation, segmentation, etc.
- Generation of the different modalities of MRI volume, e.g., T1-weighted to T2 or Flair
- Tumor generation?
- Diffusion method for data augmentation, in particular rare or hard examples, or examples in tail classes?
- CT to MRI?
- EEG signal to real image?
- Text to medical image generation? (text to 2D medical image generation, text to 3D medical image (e.g., 3D MRI data) generation)
- Text and other conditions (e.g., segmentation masks) for medical image (2D or 3D) generation using (customized) ControlNet? You may want to leverage or evaluate the some general (nature image domain) **text-to-video or image-to-video** generation models for text/image to 3D medical data (e.g., 3D MRI) generation.
- Conduct a comprehensive evaluation of the feasibility of nature image generation models (e.g., Stable Diffusion models, ControlNet) for medical image generation?

https://github.com/Warvito/generative_brain_controlnet

<https://github.com/Project-MONAI/GenerativeModels>

References:

[1] Breast Cancer Immunohistochemical Image Generation: a Benchmark Dataset and Challenge Review

<https://arxiv.org/pdf/2305.03546.pdf>

BCI dataset download:

Google

Drive: <https://drive.google.com/drive/folders/1oHxLJTjUuNoE0ZnpkyntlymTWy777EFt?usp=sharing>

[2] BCI: Breast Cancer Immunohistochemical Image Generation through Pyramid Pix2pix

https://bupt-ai-cz.github.io/BCI_for_GrandChallenge/

[3] Adaptive Supervised PatchNCE Loss for Learning H&E-to-IHC Stain Translation with Inconsistent Groundtruth Image Pairs

https://link.springer.com/epdf/10.1007/978-3-031-43987-2_61?sharing_token=8APKjymWEeqR1wAuE7YOOve4RwlQNchNByi7wbcMAY7jxNo0bliUewITgRTD3ZK5zaKOhqHCsVOERYJLgKAQ56Z9O05hje6LjixMJK0aDFGuYzXDatYEbpClGBWcpr5_IX-qttIPexkDmIT7sRVHm6YZ2wNxxU1hZxmR4SuueVw%3D

[4] Sample-Specific Debiasing for Better Image-Text Models

https://static1.squarespace.com/static/59d5ac1780bd5ef9c396eda6/t/64d1955d9ec2f716e2b44ad2/1691456861903/ID08_Research+Paper_2023.pdf

[5] EEG to fMRI Synthesis Benefits from Attentional Graphs of Electrode Relationships

https://static1.squarespace.com/static/59d5ac1780bd5ef9c396eda6/t/64d19b3e1de8702c6be95e0e/1691458369632/ID39_Research+Paper_2023.pdf

[6] Diffusion-Based Data Augmentation for Nuclei Image Segmentation

https://link.springer.com/epdf/10.1007/978-3-031-43993-3_57?sharing_token=MaKHGs4GQDpqti0okxYf8fe4RwlQNchNByi7wbcMAY7WchlOeXcjGb3IfQ5_NEou76mpPdK4IMtLPXT-qlK2YaM3Ta7H7S1TkiIFzawNz4cxLqRwWr4OwD7OjG6s5zZLzx1PLBzWzMBLe5ohff3BrZ4eewjkqeDWSMGClYF6EYk%3D

[7] Deep learning based synthesis of MRI, CT and PET: Review and analysis

2. Train or adapt large foundation models (e.g., SAM) for medical image computing

References and resources:

[1] Medical SAM Adapter: Adapting Segment Anything Model for Medical Image Segmentation
<https://arxiv.org/pdf/2304.12620.pdf>

[2] SA-Med2D-20M Dataset: Segment Anything in 2D Medical Imaging with 20 Million masks
<https://arxiv.org/pdf/2311.11969.pdf>

[3] Quilt-1M: One Million Image-Text Pairs for Histopathology [NeurIPS 2023]
(Oral)<https://github.com/wisdomikezogwo/quilt1m>

[4] BIOMEDGPT: OPEN MULTIMODAL GENERATIVE PRE-TRAINED TRANSFORMER FOR BIOMEDICINE
<https://arxiv.org/pdf/2308.09442.pdf>
<https://github.com/PharMolix/OpenBioMed>

[5] Are Large Language Models Ready for Healthcare? A Comparative Study on Clinical Language Understanding

https://static1.squarespace.com/static/59d5ac1780bd5ef9c396eda6/t/64d19a43b3b9d407b8364de4/1691458116186/ID34_Research+Paper_2023.pdf

[6] TIER: Text-Image Entropy Regularization for Medical CLIP-style models
https://static1.squarespace.com/static/59d5ac1780bd5ef9c396eda6/t/64d1a7b5bbaa8263069bdee5/1691461558916/ID128_Research+Paper_2023.pdf

[7] MA-SAM: Modality-agnostic SAM Adaptation for 3D Medical Image Segmentation
<https://arxiv.org/pdf/2309.08842.pdf>

[8] Segment Anything Model for Medical Image Segmentation: Current Applications and Future Directions <https://arxiv.org/pdf/2401.03495.pdf>

3. Pulmonary Nodule Detection and Classification in Lung CT

Summary

- Develop a deep learning model to detect and classify pulmonary nodules (benign vs. malignant) in 3D lung CT scans.
- Focus on building an automated pipeline that includes both nodule localization and classification.
- Evaluate performance using sensitivity, specificity, and detection F1 scores.

Why It's Interesting

- Early detection of malignant nodules is crucial for improving lung cancer survival rates.
- Offers the chance to explore 2D vs. 3D CNNs or advanced transformer-based architectures for volumetric data.

Dataset

- **LIDC-IDRI Dataset** (Lung Image Database Consortium and Image Database Resource Initiative)
- *Link:* <https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI>

Potential Approaches

- **3D CNN-based Detection:** Use networks such as 3D U-Net or VNet to segment and locate nodules.
- **Classification Module:** Use a secondary CNN or transformer to classify nodule patches as benign or malignant.
- **Multi-task Learning:** Combine detection and classification in one framework for efficiency.

References/Resources

1. **Data Source (LIDC-IDRI):**
<https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI>
2. **3D U-Net Paper:** Çiçek, Ö., Abdulkadir, A., Lienkamp, S.S., et al. “3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation.” *MICCAI*, 2016.
3. **Transformer for 3D:** Hatamizadeh, A., et al. “UNETR: Transformers for 3D Medical Image Segmentation.” *arXiv preprint*, 2021.

4. Diabetic Retinopathy Classification and Lesion Localization

Summary

- Use deep learning to classify retinal fundus images into different severity levels of diabetic retinopathy (DR).
- Optionally include lesion localization (e.g., microaneurysms, hemorrhages) via heatmaps or attention maps.

Why It's Interesting

- Diabetic Retinopathy is a leading cause of preventable blindness worldwide.
- Attention mechanisms or visualization techniques can show which retinal lesions influence model decisions.

Datasets

- **APTOS 2019** on Kaggle: <https://www.kaggle.com/c/aptos2019-blindness-detection>
- **Diabetic Retinopathy** Kaggle Dataset: <https://www.kaggle.com/c/diabetic-retinopathy-detection>

Potential Approaches

- **Transfer Learning:** Start with ImageNet-pretrained backbones (e.g., ResNet, EfficientNet).
- **Vision Transformers (ViT):** Explore attention-based classification for high-resolution images.
- **Lesion Localization:** Use Grad-CAM or Grad-CAM++ to generate saliency maps.

References/Resources

1. **Kaggle APTOS 2019:** <https://www.kaggle.com/c/aptos2019-blindness-detection>
2. **Kaggle DR Detection:** <https://www.kaggle.com/c/diabetic-retinopathy-detection>
3. **ViT Paper:** Dosovitskiy, A., et al. “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale.” *arXiv preprint*, 2020.

5. Automated Polyp Detection and Segmentation in Colonoscopy Images

Summary

- Build a deep learning system to detect and segment polyps in colonoscopy images or video frames.
- Evaluate using segmentation metrics (Dice, IoU) and detection metrics (precision, recall).

Why It's Interesting

- Early detection of colorectal polyps can significantly lower colorectal cancer mortality.
- Real-time detection is valuable in clinical endoscopy, placing emphasis on computational efficiency.

Dataset

- **Kvasir-SEG:** A public dataset for polyp segmentation.
- *Link:* <https://github.com/dhirajsr/Kvasir-SEG>

Potential Approaches

- **U-Net Variants** (e.g., ResUNet, UNet++): For segmentation of polyp regions.
- **Transformers or YOLO:** For real-time detection of polyps.
- **Mask R-CNN:** Combine detection and segmentation in a single pipeline.

References/Resources

1. **Kvasir-SEG Dataset:** <https://github.com/dhirajsr/Kvasir-SEG>
2. **UNet++:** Zhou, Z., Siddiquee, M.M.R., et al. "UNet++: A Nested U-Net Architecture for Medical Image Segmentation." *DLMIA*, 2018.
3. **Real-time Detection:** Explore YOLO-based methods for polyp localization in endoscopic video frames.

6. Domain Adaptation for Cross-Modality Medical Image Segmentation

Summary

- Train on one modality (e.g., MRI) and adapt the model to another modality (e.g., CT) with limited or no labels in the target domain.
- Evaluate performance by measuring segmentation accuracy (Dice, IoU) on the target modality.

Why It's Interesting

- Labeled medical data is often modality-specific and scarce.
- Domain adaptation (DA) can reduce or eliminate the need for large target-domain annotations.

Dataset

- **Multi-Modality Whole Heart Segmentation (MM-WHS) Challenge**
- *Link:* <http://www.sdspeople.fudan.edu.cn/zhuangxiahai/0/mmwhs/>

Potential Approaches

- **GAN-based DA:** Use CycleGAN or other image-to-image translation methods to align MRI and CT appearances.
- **Self-Supervised Learning:** Pretrain a model on unlabeled target images for better feature extraction.
- **Hybrid Approaches:** Combine style transfer with standard segmentation networks to handle domain shift.

References/Resources

1. **CycleGAN:** Zhu, J.-Y., Park, T., Isola, P., et al. “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks.” *ICCV*, 2017.
2. **Self-Supervised Learning:** Chen, T., Kornblith, S., Norouzi, M., et al. “A Simple Framework for Contrastive Learning of Visual Representations.” *ICML*, 2020.
3. **Domain Adaptation in Brain Lesion Segmentation:** Kamnitsas, K., et al. “Unsupervised Domain Adaptation in Brain Lesion Segmentation with Adversarial Networks.” *MICCAI*, 2017.

7. Weakly-Supervised Pathology Image Classification (Advanced)

Summary

- Perform tumor classification in whole-slide pathology images (WSIs) using only slide-level labels (e.g., “tumor” vs. “normal”).
- Employ multiple instance learning (MIL) or attention-based pooling to locate malignant regions without precise annotations.

Why It’s Interesting

- Pixel-level annotation in pathology is time-consuming and expensive.
- Weakly-supervised or MIL approaches leverage high-level labels effectively.

Dataset

- **Camelyon16 or Camelyon17** for lymph node metastasis detection
- *Link:* <https://camelyon16.grand-challenge.org/>

Potential Approaches

- **MIL Framework:** Attention-based or embedding-based multiple instance learning for slide-level classification.
- **Heatmap Generation:** Visualize suspicious regions that contribute most to the classification.
- **Self-Supervision:** Pre-train feature extractors on unlabeled histopathology patches.

References/Resources

1. **Attention-based MIL:** Ilse, M., Tomczak, J., and Welling, M. “Attention-based Deep Multiple Instance Learning.” *ICML*, 2018.
2. **Camelyon16 Dataset:** Ehteshami Bejnordi, B., et al. “Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer.” *IEEE Transactions on Medical Imaging*, 2017.
3. **Self-Supervised in Pathology:** Li, X., et al. “Self-Supervised Learning for Large-Scale Histology Image Classification.” *IEEE CVPR*, 2021.

Read MICCAI papers to find out more project ideas:

<https://conferences.miccai.org/2023/papers/categories/>

<https://papers.miccai.org/miccai-2024/>

<https://www.kaggle.com/search?q=medical+image+in%3Adatasets>

Medical Image Datasets:

- Open-Access Medical Image Repositories
 - <https://www.aylward.org/notes/open-access-medical-image-repositories>
- Computer Vision Online Image Archive – medical image
 - <https://homepages.inf.ed.ac.uk/rbf/CVonline/Imagedbase.htm#biomed>
- Google Dataset Search: <https://datasetsearch.research.google.com/>
- Kaggle dataset search: <https://www.kaggle.com/datasets>
- MedMNIST v2: A Large-Scale Lightweight Benchmark for 2D and 3D Biomedical Image Classification: <https://medmnist.com/>
- RadImageNet: An Open Radiologic Deep Learning Research Dataset for Effective Transfer Learning <https://www.radimagenet.com/>
- PatchCamelyon: The PatchCamelyon benchmark is a new and challenging image classification dataset. It consists of 327.680 color images (96 x 96px) extracted from histopathologic scans of lymph node sections. Each image is annotated with a binary label indicating presence of metastatic tissue. PCam provides a new benchmark for machine learning models: bigger than CIFAR10, smaller than imagenet, trainable on a single GPU. <https://github.com/basveeling/pcam>
- Quilt-1M: One Million Image-Text Pairs for Histopatholog [NeurIps 2023] (Oral) <https://github.com/wisdomikezogwo/quilt1m>

<https://www.kaggle.com/search?q=medical+image+in%3Adatasets>