

## Project Ideas

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

### 1. Interactive segmentation

Project goal: develop an interactive segmentation algorithm/tool for **medical image segmentation**  
Interactive image segmentation aims to extract the object-of-interest using limited human interactions such as clicks, bounding boxes, and scribbles. In this project, you can develop the click-based interaction segmentation method for medical images.

Resources:

[https://github.com/saic-vul/ritm\\_interactive\\_segmentation](https://github.com/saic-vul/ritm_interactive_segmentation)

<https://github.com/qinliuliugqin/iSegFormer>

iSegFormer: Interactive Image Segmentation with Transformers <https://arxiv.org/pdf/2112.11325.pdf>

References:

[1] <https://paperswithcode.com/task/interactive-segmentation/codeless>

[2] Interactive Image Segmentation with First Click Attention,  
[https://www.shaopinglu.net/publications\\_files/FirstClick\\_cvpr20.pdf](https://www.shaopinglu.net/publications_files/FirstClick_cvpr20.pdf)

[3] Rethinking Interactive Image Segmentation: Feature Space Annotation,  
<https://arxiv.org/pdf/2101.04378.pdf>

[4] Interactive Medical Image Segmentation with Self-Adaptive Confidence Calibration,  
<https://arxiv.org/pdf/2111.07716v1.pdf>

### 2. Brain tumor segmentation competition

**Brain Tumor Segmentation (BraTS) 2019 challenge:** It contains 335 cases of patients for training and 125 cases for validation. Each sample is composed of four modalities of brain MRI scans. Each modality has a volume of  $240 \times 240 \times 155$  which has been aligned into the same space. The labels contain 4 classes: background (label 0), necrotic and non-enhancing tumor (label 1), peritumoral edema (label 2) and GD-enhancing tumor (label 4). The segmentation accuracy is measured by the Dice score and the Hausdorff distance (95%) metrics for enhancing tumor region (ET, label 1), regions of the tumor core (TC, labels 1 and 4), and the whole tumor region (WT, labels 1, 2 and 4). The performance on the validation set assessed by the online evaluation server is usually used to validate the effectiveness of the method. However, the online evaluation server may have some issues. Therefore, 5-fold cross-validation on the training set can be conducted to evaluate the performance of the method.

**Brain Tumor Segmentation (BraTS) 2020 Challenge:** It consists of 369 cases for training, 125 cases for validation and 166 cases for testing. Except for the number of samples in the dataset, the other information about these two MRI datasets are the same.

Dataset: <https://ipp.cbica.upenn.edu/>

**Note:** You need to submit a form to request the access to download the dataset.

Resources:

- Wang, Wenxuan, et al. "Transbts: Multimodal brain tumor segmentation using transformer." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2021.
- Example Code: <https://github.com/Wenxuan-1119/TransBTS>

#### References:

- [1] Swin UNETR: Swin Transformers for Semantic Segmentation of Brain Tumors in MRI Images <https://arxiv.org/pdf/2201.01266.pdf>
- [2] TransBTS: Multimodal Brain Tumor Segmentation Using Transformer [https://link.springer.com/chapter/10.1007/978-3-030-87193-2\\_11](https://link.springer.com/chapter/10.1007/978-3-030-87193-2_11)
- [3] nnU-Net for Brain Tumor Segmentation [https://link.springer.com/chapter/10.1007/978-3-030-72087-2\\_11](https://link.springer.com/chapter/10.1007/978-3-030-72087-2_11)

### 3. Malaria Cell Stage Classification

Malaria has four life stages: Ring, Trophozoite, Schizont, and Gametocyte.

Dataset: <https://github.com/QaziAmmar/A-Dataset-and-Benchmark-for-Malaria-Life-Cycle-Classification-in-Thin-Blood-Smear-Images>

The dataset statistics are:

Healthy RBCs=37899

Ring=164

GametoCyte=261

SchiZont=27

Trophozoite=77

Difficult=21

Since these types of data (Ours and also in the real world) are highly imbalanced, i.e., a few abnormal cells and the rest are normal, the students can work on two research problems.

1) Abnormal Cell Detection: The model would be trained on normal cells only and the task would be to detect abnormal (malarial cells in our case) cells during testing.

2) Improved Cell Stage Classification Under Imbalance data scenario.

Malaria has four life stages: Ring, Trophozoite, Schizont, and Gametocyte. In which trophozoite and schizont are very rare

Since the data is highly imbalanced, the students are supposed to use/design methods to achieve improved classification results for the rare classes.

#### References:

- [1] A Dataset and Benchmark for Malaria Life-Cycle Classification in Thin Blood Smear Images Qazi Ammar Arshad, Mohsen Ali, Saeed-ul Hassan, Chen Chen, Ayisha Imran, Ghulam Rasul, Waqas Sultani Neural Computing and Applications, 2021
- [2] Example code: <https://github.com/QaziAmmar/A-Dataset-and-Benchmark-for-Malaria-Life-Cycle-Classification-in-Thin-Blood-Smear-Images>

#### 4. Pill Image Classification



Project goal: develop deep learning-based methods for pill image recognition

Dataset and resources:

ePillID Benchmark: <https://github.com/usuyama/ePillID-benchmark>

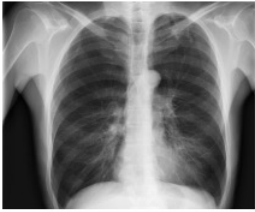
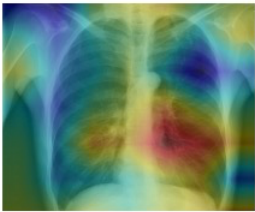
ePillID Dataset: A Low-Shot Fine-Grained Benchmark for Pill Identification,  
<https://arxiv.org/pdf/2005.14288.pdf>

Follow the same training and valuation protocols to evaluate your method.

References:

[1] Fast and accurate medication identification, <https://www.nature.com/articles/s41746-019-0086-0.pdf>

#### 5. Pneumonia Detection on Chest X-Rays (or other medical image modalities such as CT and MRI) with Deep Learning


<b>Input</b> Chest X-Ray Image
<b>CheXNet</b> 121-layer CNN
<b>Output</b> Pneumonia Positive (85%)


Project goal: develop a deep learning model that can automatically detect pneumonia from chest X-rays (or other imaging modalities such as CT).

Resources and Datasets:

1. <https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/overview>
2. <https://www.eibir.org/covid-19-imaging-datasets/>
3. COVID-19 Radiography Database: <https://www.kaggle.com/tawsifurrahman/covid19-radiography-database>
4. COVID-19 Image Data Collection (Paper with Code): <https://paperswithcode.com/dataset/covid-19-image-data-collection>

References:

- [1] Jia, Guangyu, Hak-Keung Lam, and Yujia Xu. "Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method." *Computers in biology and medicine* 134 (2021): 104425.
- [2] Nguyen, Dan, et al. "Deep learning-based COVID-19 pneumonia classification using chest CT images: model generalizability." arXiv preprint arXiv:2102.09616 (2021).

6. Generative models (e.g., GANs, diffusion models) for medical image analysis (e.g., image segmentation, image generation)

Text to image generation:

RoentGen: Vision-Language Foundation Model for Chest X-ray Generation  
<https://arxiv.org/pdf/2211.12737.pdf>

Image to image translation:

Conversion Between CT and MRI Images Using Diffusion and Score-Matching Models  
<https://arxiv.org/pdf/2209.12104.pdf>

Resources:

<https://github.com/amirhossein-kz/Awesome-Diffusion-Models-in-Medical-Imaging#image-to-image-translation>  
<https://github.com/xinario/awesome-gan-for-medical-imaging>  
Diffusion Models for Medical Image Analysis: A Comprehensive Survey  
<https://arxiv.org/pdf/2211.07804.pdf>  
Generative Adversarial Network in Medical Imaging: A Review  
<https://arxiv.org/pdf/1809.07294.pdf>  
The Role of Generative Adversarial Network in Medical Image Analysis: An In-depth Survey  
<https://dl.acm.org/doi/10.1145/3527849>

7. Federated learning for medical image analysis

Resources:

<https://github.com/albarqouni/Federated-Learning-In-Healthcare>  
<https://github.com/monk1337/Aweome-Heathcare-Federated-Learning>  
Federated Learning for Smart Healthcare: A Survey  
<https://arxiv.org/pdf/2111.08834.pdf>

## 8. Self-supervised learning for medical image analysis

Resources:

Dive into Self-Supervised Learning for Medical Image Analysis: Data, Models and Tasks

<https://arxiv.org/pdf/2209.12157.pdf>

<https://github.com/SaeedShurrah/awesome-self-supervised-learning-in-medical-imaging>

<https://github.com/funnyzhou/A4SM>

[https://github.com/tqxli/self\\_supervised\\_learning\\_in\\_medical\\_imaging](https://github.com/tqxli/self_supervised_learning_in_medical_imaging)

## 9. ASD (Autism spectrum disorder) analysis

### Problem behavior recognition in videos

Problem Behaviors Recognition in Videos using Language-Assisted Deep Learning Model for Children with Autism

<https://arxiv.org/pdf/2211.09310.pdf>

Notes:

1. How to improve the generalization ability of the recognition model? (e.g., cross-dataset evaluation)
2. Can we collect a much larger dataset for this application? (available resources: existing datasets plus self-collected videos from YouTube).
3. Can we extend the task of action recognition to action localization? (localize the problem behavior temporally in a long video)

Datasets for ASD behavior recognition in videos

ESDB: <https://drive.google.com/file/d/1r41e17ZfoGCVykou4Yr4QGoTgLYkqE2C/view?usp=sharing>

SSDB:

[https://drive.google.com/file/d/1tQ89MXK4TXYTXPV8Gtk86I\\_tNM8VrCXU/view?usp=sharing](https://drive.google.com/file/d/1tQ89MXK4TXYTXPV8Gtk86I_tNM8VrCXU/view?usp=sharing)

Bidirectional Cross-Modal Knowledge Exploration for Video Recognition with Pre-trained Vision-Language Models <https://arxiv.org/pdf/2301.00182.pdf>

### Eye Movements for the Children with Autism Spectrum Disorder

H. Duan, G. Zhai, X. Min, Z. Che, Y. Fang, X. Yang, J. Gutiérrez, P. Le Callet, "A Dataset of Eye Movements for the Children with Autism Spectrum Disorder", ACM Multimedia Systems Conference (MMSys'19), Jun. 2019.

Dataset: <https://zenodo.org/record/2647418#.Y78ezezMJeg>

More related references:

Visual Attention Analysis and Prediction on Human Faces for Children with Autism Spectrum Disorder [https://duanhuiyu.github.io/files/2019TOMM\\_duan.pdf](https://duanhuiyu.github.io/files/2019TOMM_duan.pdf)

**Related Workshops at CVPR 2023 for submitting your research works on this topic:**

i) 4<sup>th</sup> Workshop of Face and Gesture Analysis for Health Informatics

Workshop website is not online yet, but the previous edition can be found here:

<http://fgahi.isir.upmc.fr/index.php?perma=1508224960>

ii) International Workshop on Computer Vision for Physiological Measurement

Workshop website is not online yet, but the previous edition can be found here:  
<https://www.es.ele.tue.nl/cvpm22/cfp.php>

### Other resources to look for project ideas:

- Look for topics from conference proceedings
  - Example:
  - MICCAI 2021 and 2022 accepted papers by topics:  
<https://miccai2021.org/openaccess/paperlinks/categories/index.html>
  - <https://conferences.miccai.org/2022/papers/categories/>
- Conference workshops
  - MICCAI Workshops: <https://www.miccai2021.org/en/MICCAI2021-WORKSHOPS.html>
  - <https://conferences.miccai.org/2022/en/MICCAI2022-WORKSHOPS.html>
  - MICCAI Challenges: <https://www.miccai2021.org/en/MICCAI2021-CHALLENGES.html>
  - <https://conferences.miccai.org/2022/en/MICCAI2022-CHALLENGES.html>
  - CVPR 2021 Medical Computer Vision Workshop:  
<https://sites.google.com/view/cvprmcv21>
  - ICCV 2021 Workshop - AI-enabled Medical Image Analysis Workshop and Covid-19 Diagnosis Competition (MIA-COV19D): <https://mlearn.lincoln.ac.uk/mia-cov19d/>
  - ICCV 2021 Workshop - Computer Vision for Automated Medical Diagnosis:  
<https://sites.google.com/view/cvamd2021/home?authuser=0>
- Kaggle Competitions
- **Grand Challenge: A platform for end-to-end development of machine learning solutions in biomedical imaging.** <https://grand-challenge.org/>
- Ideas inspired by the papers you read
- Projects ideas that are related to your research (e.g., topics related to your MS thesis or Ph.D. dissertation)

### 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/>