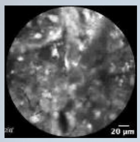

Deep Tissue Characterisation for Surgical Resection Guidance in Robot-assisted Neurosurgery using Endomicroscopic Data

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Abstract

The main goal of brain tumor resection is to achieve complete resection of the tumor with minimal damage to nearby healthy tissues and vasculature. Probe-based Confocal Laser Endomicroscopy(pCLE) has been used to promote the maximum safe resection of brain tumor. However, it is difficult to interpret pCLE images, even for experienced surgeons. The classification of these images is of significance to be studied. The key application of this project is to classify healthy and different types of cancerous brain tumors based on the images of pCLE.

Introduction

Dataset

- 2-classes Ex-vivo videos: Contains instances of Glioblastoma(GBM) and Meningioma(MNM). All frames are considered as *diagnosticable*.
- 4-classes In-vivo videos: Contains instances of Glioblastoma(GBM), Meningioma(MNM), Astrocytoma(ASC) and healthy(H). Some frames can be classified as *non-diagnosticable*. Only a few samples of patients in each class.

Aim

Achieve automatic classification which will help the surgeon to make diagnosis of brain tumor.

Motivation

Current study of the guidance of in vivo brain tumor classification is limited.

Challenges

•There are many non-diagnosticable instances in the In-vivo dataset, which have a negative impact on classification performance.
•Insufficient number of labeled in-vivo samples are used for machine learning to achieve accurate diagnosis of newly collected in-vivo cases.

Solutions

•Eliminate the non-diagnosticable instances recognized by a few-shot network in the in-vivo dataset.
•Train a few-shot learning network that can achieve high-performance classification on in-vivo dataset.

Objective

•Dataset Cleaning - A Deep Nearest Neighbor(DN4) few-shot network used to identify diagnosticable and non-diagnosticable instances in the in-vivo dataset [1].
•Classification - A Few-shot Learning with Embedding Adaptation of Transformer(FEAT) network used to classify the cleaned in-vivo dataset into 4 classes of GBM, MNM, ASC, H [2].

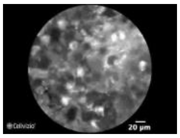

Fig 1. example of diagnosticable image.

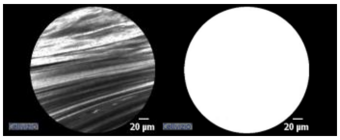

Fig 2. Examples of non-diagnosticable image.

Preliminary results

The accuracy of the original In-vivo dataset and the cleaned in-vivo dataset under FEAT classification is reported in Table 1, the result is the classification accuracy of GBM and MNM:

	FEAT(with backbone trained on In-vivo)	FEAT(with backbone trained on Ex-vivo)
Accuracy	85.42%	81.59% 91.61% (cleaned dataset)

The accuracy of the original In-vivo dataset and the cleaned in-vivo dataset under FEAT classification is reported in Table 2, the result is the classification accuracy of ASC and MNM:

	FEAT(with backbone trained on In-vivo)	FEAT(with backbone trained on Ex-vivo)
Accuracy	86.53%	82.24% 99.63% (cleaned dataset)

Method

The overall process of this project is to first clean up the in-vivo dataset, and then use the cleaned data for few-shot learning(FEAT) to make classification.

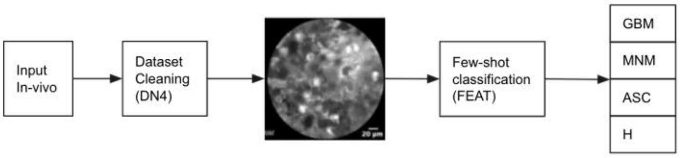

Fig 3. Project flow

Dataset Cleaning

- DN4 was first used to train to classify ex-vivo datasets (GBM, MNM).
- The trained DN4 model was directly transferred to classify the diagnosticable images in the in-vivo dataset, by using the 'learn-to-learn' feature of few-shot learning.

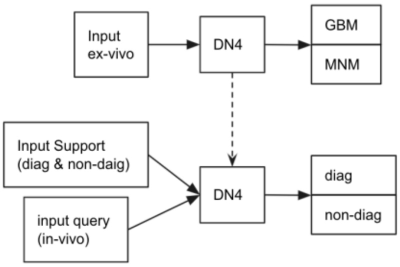

Fig 4. In-vivo dataset cleaning using transferred trained DN4 model

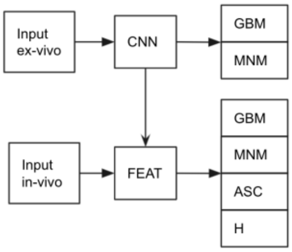

Fig 5. FEAT was used to classify in-vivo data

In-vivo Data Classification

- Use ex-vivo data to do CNN pre-training to get backbone.
- Use FEAT to train in-vivo data based on the backbone.

Future work

1. Fine-tune the pre-trained model instead of train from scratch over the ex-vivo data. In order to enhance the performance of the pre-trained model and further improve the accuracy of the FEAT network.
2. Evaluate the dataset cleaning performance by train the cleaned data using DN4 and compare the results with previous work in this area.
3. Modify the set-to-set function and the classification function to enhance the performance of FEAT.
4. Try and compare the performance with other state-of-art few-shot learning network like CrossTransformers [3].

References

[1] W. Li, L. Wang, J. Xu, J. Huo, Y. Gao and J. Luo, "Revisiting Local Descriptor based Image-to-Class Measure for Few-shot Learning", *arXiv.org*, 2019. [Online]. Available: https://arxiv.org/abs/1903.12290.
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