**Multimodal Joint Fusion of Imaging Modalities for INPH Diagnosis**

**Purpose**

A Higher-Level Gait Disorder (HLGD) is one of the typical symptoms seen in Idiopathic Normal Pressure Hydrocephalus. The pathophysiology of this disease is still not entirely understood, including how morphological changes, such as enlargement of the cerebral ventricles, relate to the development of symptoms. Deep learning methods now offer a possibility to perform objective whole-brain analysis. To clarify the relationship between brain morphology and higher-level gait disorder (HLGD), we evaluate a cohort of older people, with and without gait disorder, not selected based on established radiological signs of INPH. If uninfluenced deep learning analysis applied to the brain MR-images of this unbiased cohort can differentiate between subjects with HLGD and controls, it would provide evidence that there is a link between the HLGD-symptoms and brain morphology deviations.

**Medical Research Question:**

Is there a link between symptoms and brain morphology deviations?

**Technical Research Question:**

* Exploration and comparison of multiple Joint Fusion techniques to exploit inter- and intra- modality correlations to understand the best of *how* to join two modalities to overcome a specific classification task.
* Comparison of the multimodal models developed with standard unimodal models to understand the utility of the multimodality.

**Materials**

The VESPR (Ventriculomegaly and Gait Disturbance in the Senior Population in the Region of Västerbotten) population-based study included a large cohort of older people with and without gait disorder, who underwent clinical investigation and assessment of gait. 73 patients with gait disorder classified as HLGD and 146 participants without gait disorder were included in this study. T1-weighted and T2-FLAIR brain images were obtained for all participants as 3D volumes. In the pre-processing phase, the volumes were co-registered to MNI space (Montreal Neurological Institute, ICBM152: <http://nist.mni.mcgill.ca/icbm-152lin/>), resliced and skull-stripped.

**Methods**

1. Study of the state-of-the-art of joint fusion methods for imaging modalities
2. Development of multiple deep neural networks which use joint fusion between CNNs:
   1. Concatenation
   2. Kronecker:
   3. MMTM
   4. Cross Stitch
   5. ecc…
3. Development of standard unimodal CNNs with comparison with multimodal networks

**Literature**

* Multimodal Deep Learning
  + A survey on deep multimodal learning for computervision-advances, trends, applications, and datasets-2022
  + Beyond Medical Imaging- A Review of Multimodal Deep Learning in Radiology-2021
  + Deep multimodal learning-A survey on recent advances and trends-2017
  + Multimodal deep learning for biomedical data fusion- a review-2022
  + Multimodal Deep Learning-2011
  + Multimodal machine learning-A survey and taxonomy-2018
* Joint Fusion
  + Pathomic Fusion: An Integrated Framework for Fusing Histopathology and Genomic Features for Cancer Diagnosis and Prognosis-2019
  + i-Code- An Integrative and Composable Multimodal Learning Framework-2022
  + MMTM Multimodal Transfer Module for CNN Fusion-2020
  + Tensor Fusion Network for Multimodal Sentiment Analysis-2017
  + Cross-stitch Networks for Multi-task Learning-2016

**Tools**

* Python
* PyCharm (IDE per Python)
* Git: per versionamento codice
* PyTorch: libreria python per Deep Learning
* GPU: Alvis Super Computer