

M2 Internship + PhD opportunity Deep Learning / Neuroimagerie

Uncertainty-informed multimodal fusion pour la segmentation du thrombus et des lésions ischémiques en IRM

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Durée : 5–6 mois – **Période :** Février à Août 2026 – **Rémunération :** €3600

Subject Develop an uncertainty-informed multimodal fusion approach for thrombus and ischemic lesion segmentation on MRI in acute ischemic stroke. The project leverages SWAN/PHASE, DWI/ADC, and TOF-MRA to synthesize hypoperfusion-relevant information and improve clinical decision support [1–5].

Position of the problem Stroke is the leading cause of acquired disability in adults and the second leading cause of death worldwide [6]. In ischemic stroke, a thrombus occludes a cerebral artery, depriving downstream tissue of oxygen. Treatment selection (thrombectomy or thrombolysis) requires accurate clot localization and estimation of the ischemic area from hyperacute multimodal MRI [1–5]. However, signal variability, partial redundancy across modalities, and low-contrast/high-noise regions introduce *segmentation uncertainty* that limits clinical accuracy [7–9]. Prior cross-modal attention work achieved reliable thrombus detection (rate ≈ 0.97) but only Dice ≈ 0.65 , underscoring the need to make uncertainty an explicit variable in fusion.

Internship objectives A segmentation model based on cross-modal attention enabled reliable thrombus detection (rate ≈ 0.97) but achieved a Dice ≈ 0.65 , highlighting the need to address uncertain regions. The intern will help implement an uncertainty-aware multimodal fusion system to improve thrombus and ischemia segmentation.

- **Uncertainty map generation.** Compute voxel-wise entropy/Bayesian variance maps to identify high-uncertainty zones (e.g., thrombus borders) :

$$U_{\text{entropy}}(x) = - \sum_c p_c(x) \log p_c(x),$$

leveraging Bayesian deep learning tools for calibrated uncertainty [7–9].

- **Uncertainty-guided attentive fusion.** Inject uncertainty maps as attention masks and *focus inter-modal fusion* where uncertainty is high so secondary modalities add complementary evidence (compatible with modern biomedical backbones such as U-Net) [10].
- **Localized diffusion regularization (“focused blurring”).** Apply a Gaussian blur weighted by local uncertainty and train a diffusion model on blurred images to reinforce contextual learning near the thrombus :

$$I_{\text{blurred}}(x) = (I * G_{\sigma(x)})(x), \quad \sigma(x) \propto U(x),$$

using recent denoising diffusion frameworks [11].

- **Backbones & estimators.** Use 3D U-Net / Cross-Modal Attention Network / Diffusion Model; estimate uncertainty via MC-dropout, deep ensembles, and Bayesian learning [7–9]; quantify cross-modal information with mutual information

$$I(M_1; M_2) = H(M_1) + H(M_2) - H(M_1, M_2),$$

and partial information decomposition (PID) to dissect redundancy, complementarity, and synergy [12, 13].

- **Experimental comparison.** Compare focused blur vs. global uniform blur; assess Dice, sensitivity, and clinical precision (with modality-specific cues from SWI/PHASE, DWI/ADC, and TOF-MRA) [1–5].

Application & Expected Impact

- **Datasets & setup.** Multimodal MRI from stroke patients (**SWAN/PHASE**, **DWI/ADC**, **TOF-MRA**); experiments on **CHSF**, **MATAR**, and **ISLES2022**. Environment : PyTorch/Python, RTX 3090, CHSF-IBISC collaboration.
- **Clinical utility.** Improved thrombus and ischemia segmentation enables more reliable estimation of penumbral “mismatch,” supporting **reperfusion triage** when onset is uncertain and enhancing **treatment benefit prediction**.
- **Deliverables.** (i) Prototype of an uncertainty-guided multimodal segmentation model; (ii) quantitative analysis linking uncertainty to mutual information; (iii) visual reports of clinically high-uncertainty regions; (iv) manuscript targeting *IEEE TMI* or *Frontiers in Neuroinformatics*.

Expected results

- Prototype of an uncertainty-guided multimodal segmentation model;
- Quantitative analysis of the link between uncertainty and mutual information;
- Reporting and visualization of clinically high-uncertainty regions;
- Preparation of a manuscript for *IEEE Transactions on Medical Imaging* or *Frontiers in Neuroinformatics*.

Candidate profile We look for strongly motivated candidates (i) coming from a math, physics, computer science or engineering diploma (ii) having a strong mathematical background, notably in linear algebra, analysis, probability and statistics, in machine learning and deep learning (iii) having good programming skills on some scientific language, preferably python.

Knowledge of medical imaging, particularly MRI, is not required, but is a strong plus. Knowledge of basic optimization theory is also appreciated.

Practical information The intern will be mainly hosted at the UFR science and technology (40 rue du Pelvoux) close to the city center. However, he/she may also spend some periods at the Hospital of Corbeil.

The monthly internship gratification is of about €670.

Application procedure : send a motivation letter, a CV and your University transcript (relevé de notes) since 1st year BSc to {vincent.vigneron,hichem.maaref}@univ-evry.fr.

What we offer Hands-on experience with cutting-edge AI techniques for medical imaging.

Tackle real-world, high-impact healthcare problems using deep learning.

Close mentorship from experienced researchers at the IBISC laboratory.

Opportunities to co-author publications and present your work at conferences.

Continuation into PhD studies

Contact {hichem.maaref, vincent.vigneron}@ibisc.univ-evry.fr, congej@yahoo.fr

Références

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