Brain Stroke Analysis from Non-Contrast CT and Path-Planning for Robot-Assisted Surgical Intervention

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Highlights of the Project

Objectives

- To **detect** the presence of, localize, and segment **stroke regions** from NCCT volumes.
- To devise a **path-planning strategy for surgical intervention** using a robotic arm.
- To enable clinicians to **visualize** stroke region and planned-path **using a web application.**

Distinguishing Features

- **Multi-dimensional feature** fusion for **context-aware** segmentation,
- **Improvements to Q-learning** for robotic path-planning to attain faster convergence.

Dataset & Environment

- Benchmark **Intracranial Hemorrhage Dataset** [1] comprising **2500 brain window images** collected from **82 patient samples**.
- **Three-dimensional workspace** with rectangular obstacles and target defined in the xyz-space, chosen to represent a **realistic surgical environ.**

User Interface

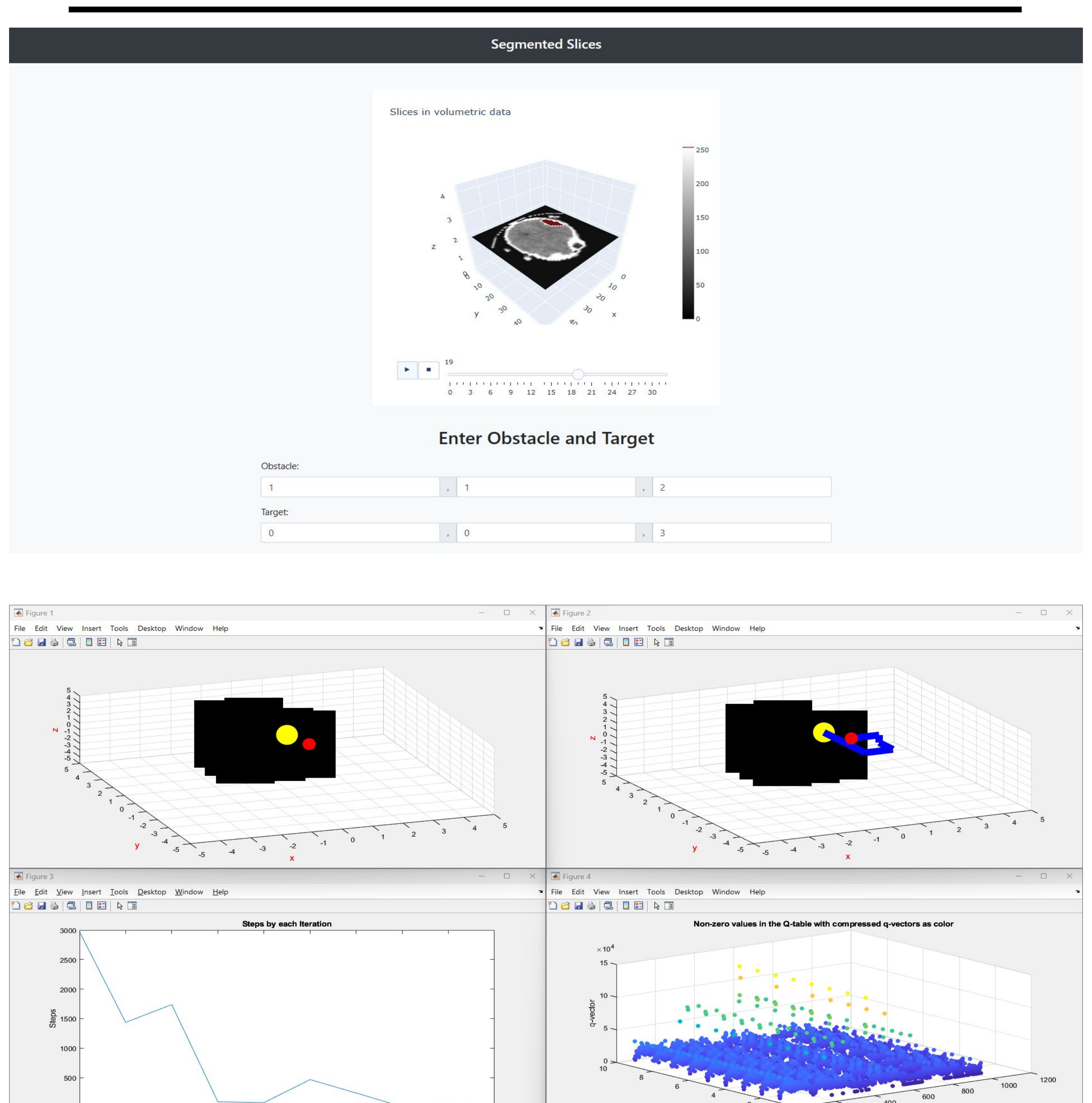

Figure 1. Screenshots from the visualization web-app

Proposed Method

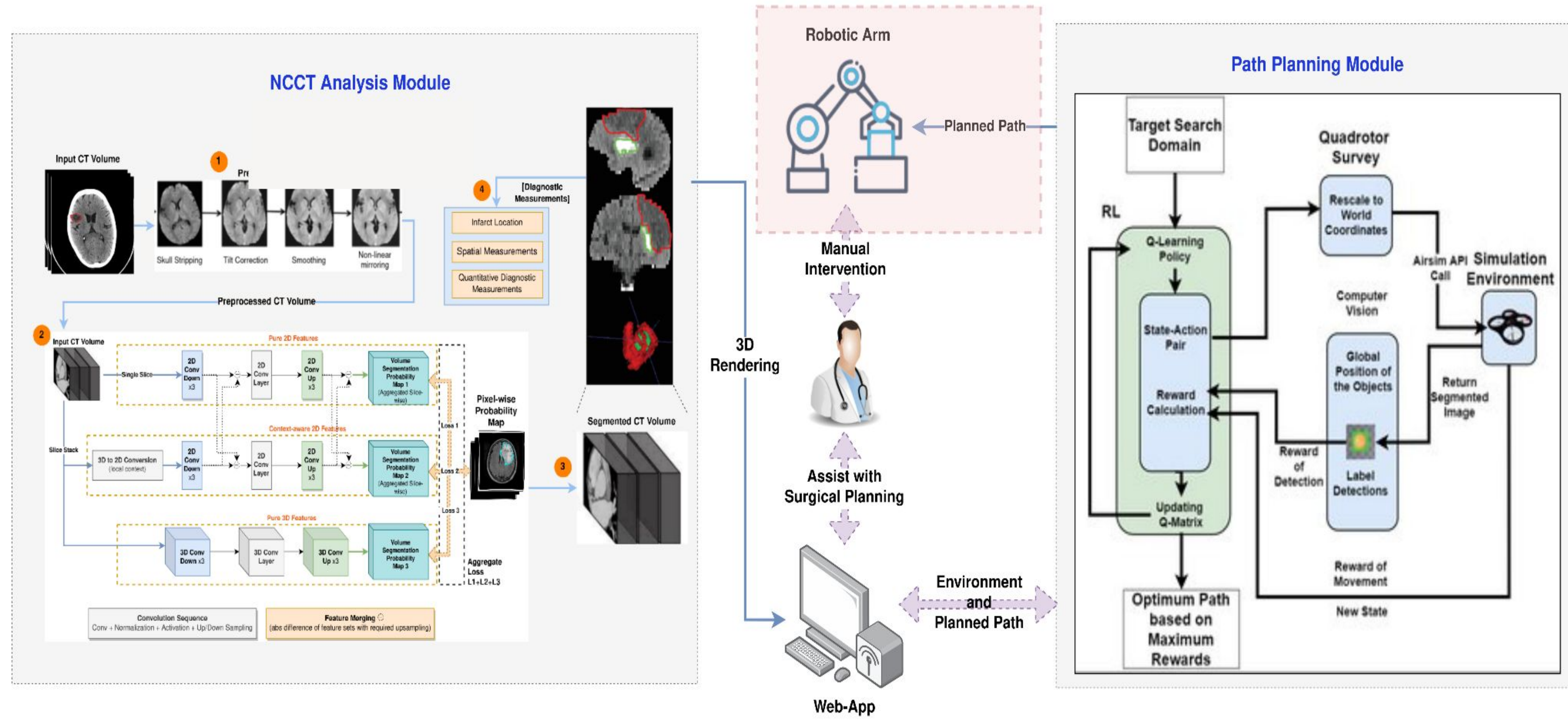

Figure 2. Overall architecture and workflow of the proposed system

Module 1: Stroke Region Detection

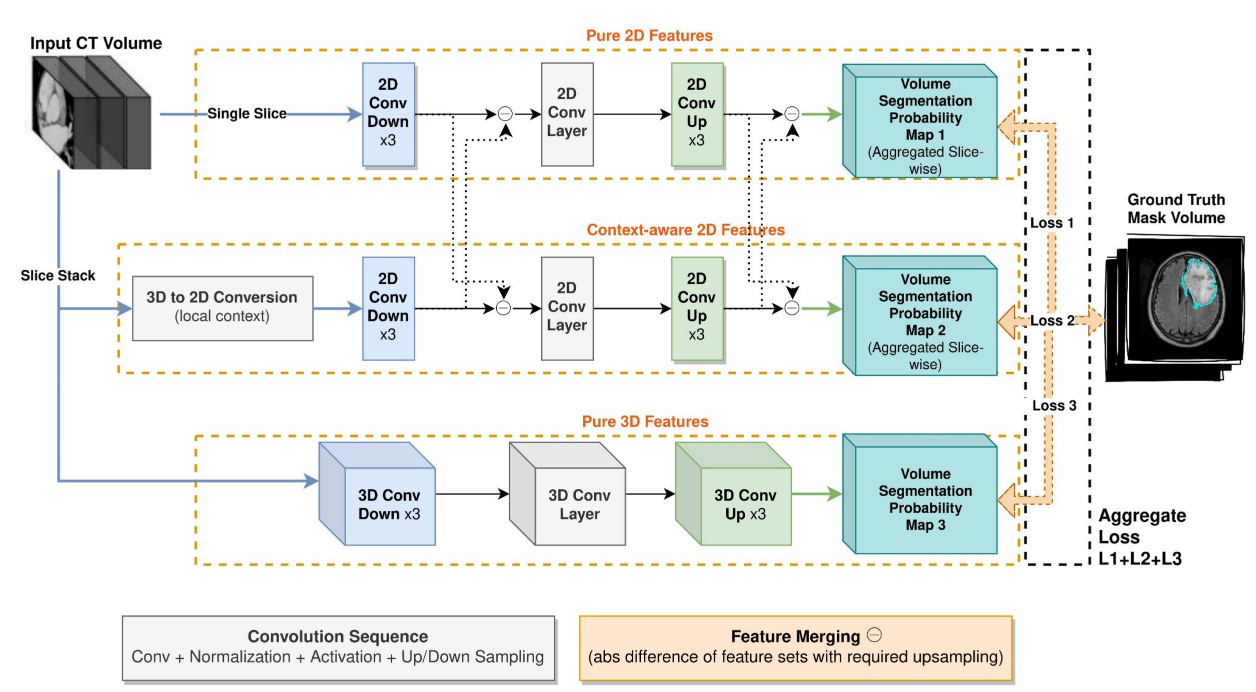

Figure 4. Proposed neural network for segmentation

- **Three** concurrent image processing **pathways**,
  - Pure 2D features.
  - Context-aware 2D features.
  - Pure 3D features.
- **Feature merging** between the 2D pathways, akin to skip connections in *UNets* and *ResNets*.
- **Aggregated losses** and **averaged probability map** to combine posterior inference from all pathways.
- **Overcomes pitfalls** associated with **isolated 2D and 3D** scan processing.

Module 2: Enhanced Q-Learning for Path-planning

$$P(\Delta E, T(t)) = \exp\left(-\frac{\Delta E}{T(t)}\right)$$

$$T(t) = T_0 \cdot \alpha^t$$

Equation 1. Simulated annealing for exploratory actions

$$\max\left(\max_{i=1}^{n}|u_i - v_i|,\ \left(\sum_{i=1}^{n}|u_i - v_i|^p\right)^{1/p} - \left(\sum_{i=1}^{n}|u_i' - v_i'|^p\right)^{1/p}\right)$$

$$||\text{current arm position - target}||^2 - ||\text{previous arm position - target}||^2$$

Equation 2. Novel distance metric for arm position

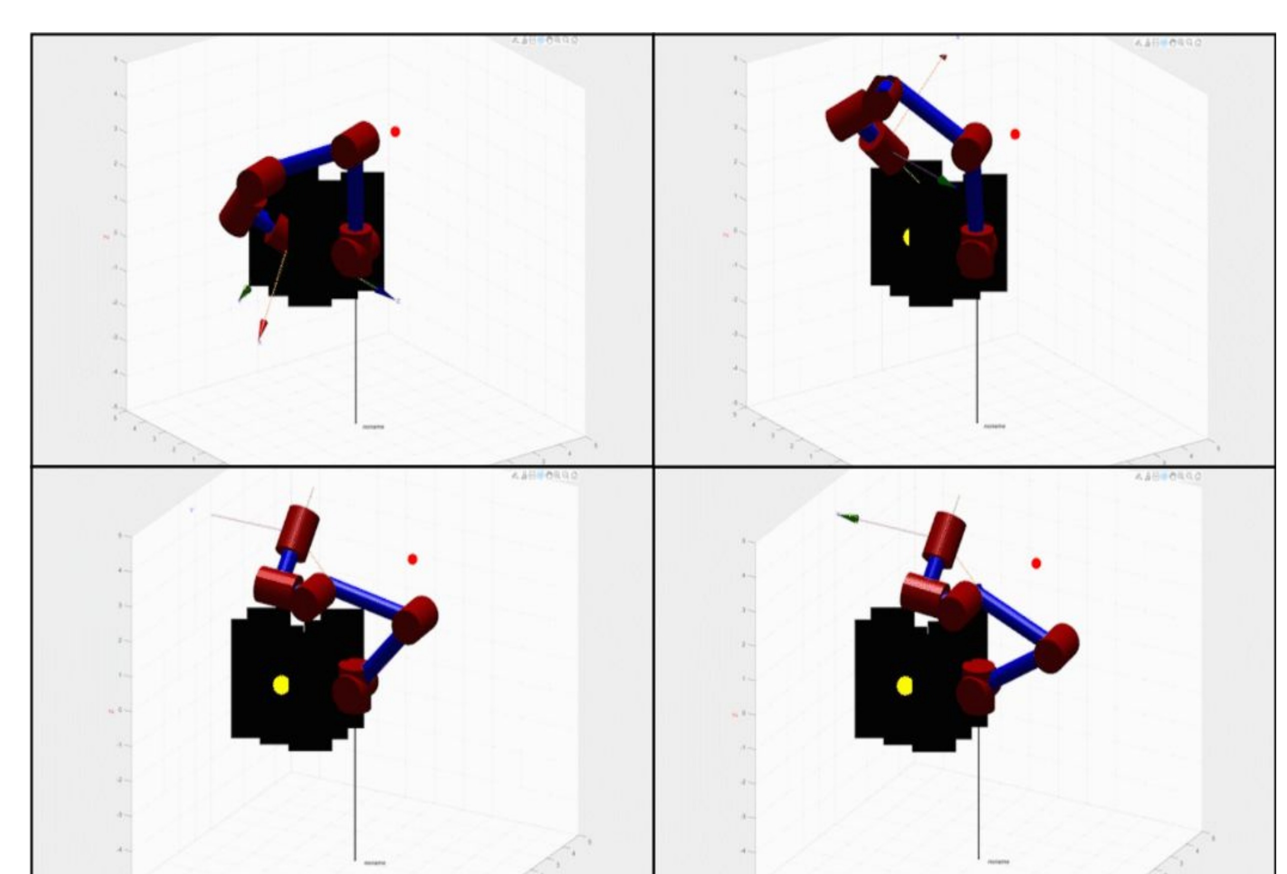

Figure 5. Intermediate steps of the robotic arm

Performance Analysis

Approach	Backbone	Dataset	DSC	Mean IoU	AuROC
FPN	EffNet-B0	Peer-Reviewed Intracranial Hemorrhage Dataset Hssayeni et al. (2020)	41.18%	28.20%	-
UNet	EffNet-B0		46.73%	30.42%	-
PSPNet			40.21%	27.51%	-
DeepLabV3+			33.82%	17.43%	-
Best UNet *			44%	27.5%	-
AutoEncoder+ChanVese [2]*			70%	-	-
M-Net			70.41%	59.95%	86.13%
Proposed			**76.11%**	**64.52%**	**89.15%**

Table 1. Quantitative comparison of segmentation

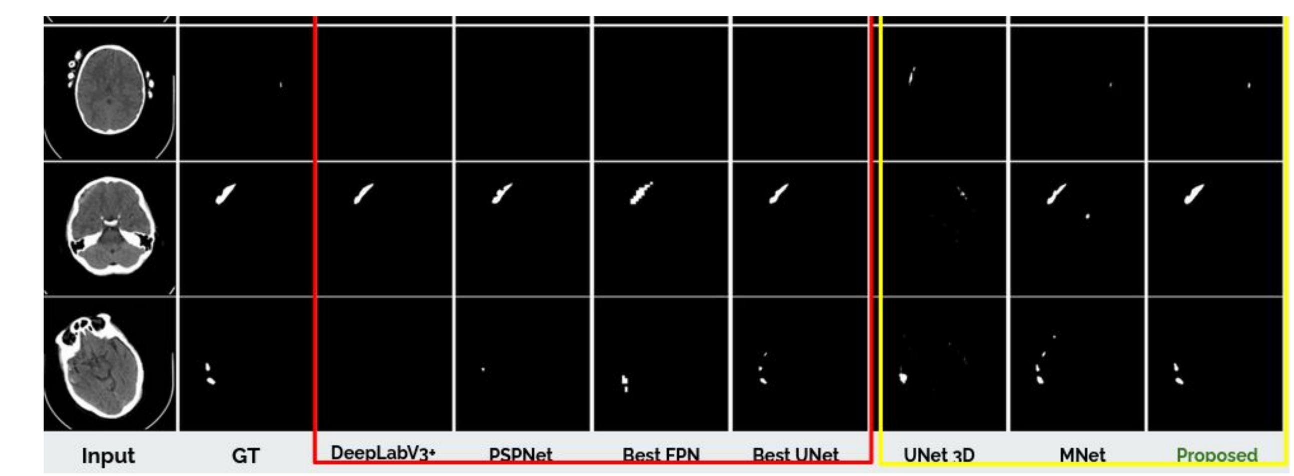

Figure 6. Qualitative comparison of segmentation

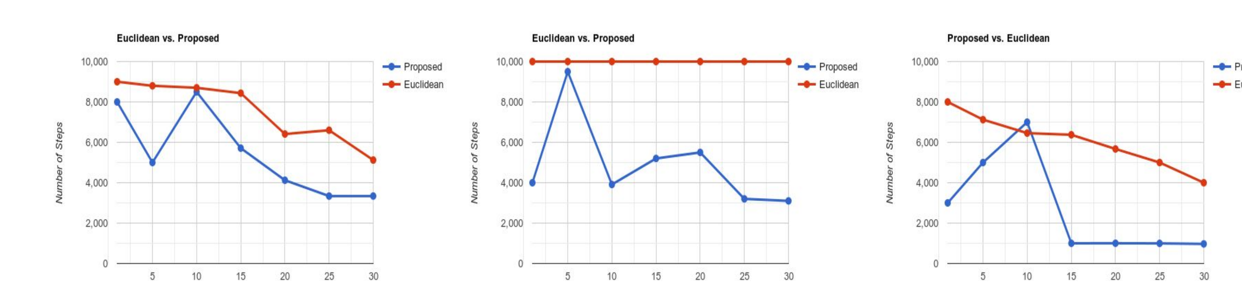

Figure 7. Performance of proposed distance metric

Inferences

- A **novel neural network is proposed** for segmenting stroke regions from NCCT volumes that leverages **context-awareness and pure dimensional features.**
- After analyzing multiple path-planning strategies, a **modified Q-learning algorithm is proposed** for robotic surgical inerventions.
- A **web-app** was developed to **visualize identified stroke regions** and the **planned robotic path.**

References

[1] Murtadha Hssayeni, MS Croock, AD Salman, HF Al-khafaji, ZA Yahya, and B Ghoraani. Computed tomography images for intracranial hemorrhage segmentation. Intracranial Hemorrhage Segmentation Using A Deep Convolutional Model. Data, 5(1):179, 2020.

[2] Erdal Baskaran, Zafer Comert, and Yuksel C ¸ elik. Convolutional neural network approach for automatic tympanic membrane detection and classification. Biomedical Signal Processingl, 56:101734, 2020.