Brain Stroke Analysis from Non-Contrast Brain CT and Path-planning for Robot-assisted Thrombectomy

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Introduction

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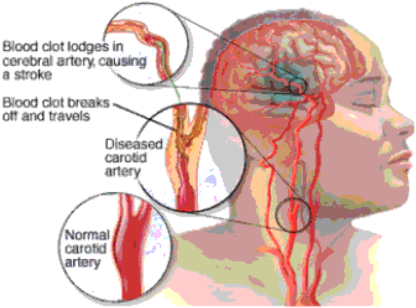
- A stroke is a medical emergency. Prompt treatment is crucial to reduce brain damage and other complications.
- There are *two prominent causes of stroke*: a blocked artery (**ischemic stroke**), or leaking or bursting of a blood vessel (**hemorrhagic stroke**).



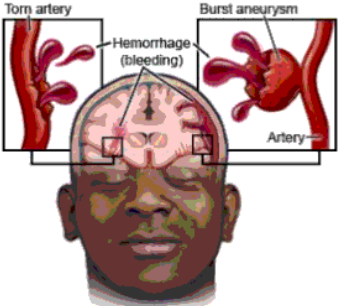


Figure: Depiction of Ischemic Stroke (left) and Hemorrhagic Stroke (right).

Introduction

- The identification of the stroke type is crucial to treatment decisions.
- *Computed Tomography (CT)* and *Magnetic Resonance Imaging (MRI)* are the typical imaging methods in screening stroke patients.
- However, for **rapid diagnosis** and treatment, crucial for **acute strokes**, CT is a faster, easily-available, and cost-effective modality – hence, it is more widely used [1].
- *Thrombectomy*, the invasive excision of a clot, is the preferred treatment for Ischemic Strokes.
- Treatment of Hemorrhagic Strokes is more complex and case-specific, and is not the focus of this study beyond the level of type identification.

Problem Statement

Problem Statement

A. Differentiate: *Ischemic Stroke* Vs. *Hemorrhagic Stroke*
B. Localize and Visualize the site of stroke origin

- 3D reconstruction of CT-series.
- Simultaneous segmentation correction localization of stroke infarct.
- ML-assisted algorithm to identify the stroke type.
- Rendering a 3D visualization of the stroke epicenter and context.

For cases of **Ischemic Stroke**,

C. Perform path-planning for robot-assistive thrombectomy

- Supervised autonomous operation to excise the clot.
- Interventional surgical staff provides onsite supervision.
- Reconstructed CT is used to guide the robot, and the surgical staff.
- Computational Vascular Model and CT-configured simulation environment to test the robot on specific cases of stroke.

Problem Statement

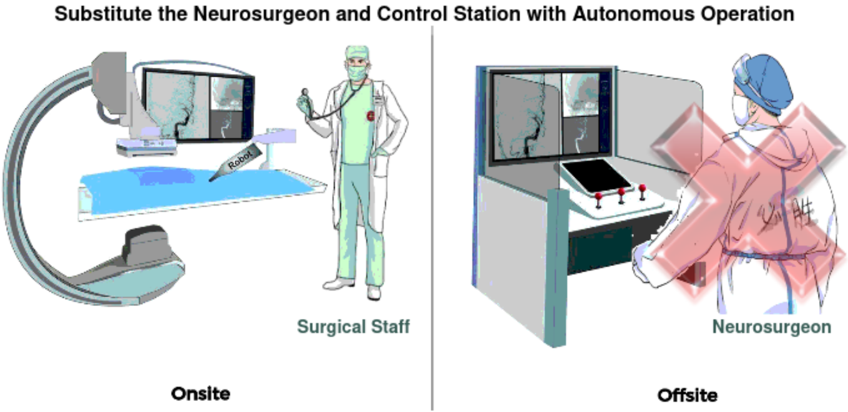


Figure: Role of the assistive robot, and introduction of autonomous capabilities.

Justification of the Statement

Justification of the Statement

The Need to Differentiate Stroke Types

- The strokes manifest through *nearly identical symptoms*.
- The causes, and consequently, the treatments for the two types of stroke are *strikingly different*.
- *Ischemic stroke* is treated with *blood-thinning* drugs to dissolve the clot.
- *Hemorrhagic stroke* requires major surgery. *Coagulants* are injected.
- Administering the *incorrect class of drug* will certainly and immediately *exacerbate the stroke*.

Definitions

Ischemic: Blood supply to part of the brain is interrupted by a clot.
Hemorrhagic: A ruptured blood vessel causes bleeding inside the brain.

Justification of the Statement

State of and Research Gaps in Stroke Type Differentiation

- Limited investigation of the third axis — prediction models frequently miss stroke sites that span the third axis.
- Existing models apply Machine Learning (ML) directly — not interpretable and hard to verify the decision basis of ML models.
- Existing predictors, ML or otherwise, working on 3D CTs have high inference times and achieve one single objective.
- Pure NCCT-based analysis is less explored than perfusion CTs and weighted MRIs.

- Simplified class hierarchy for this use-case.
- 3D reconstruction to detect cross-slice stroke sites.
- Simultaneous analysis and correction when stacking slices to reconstruct 3D volume [2].

Justification of the Statement

The Need for Robotic Assistance and Operation

"It should be possible to treat a diagnosed case of **ischemic stroke** *from a close-by center remotely by specialized interventional staff"*

- Thrombectomy is the preferred treatment. Reduces post-operative repercussions compared to conventional thrombolytic methods.
- Over 80% of world population **cannot** reach a thrombectomy-capable center within 1-hour of stroke onset [3].
- Manual laparoscopic approaches often cause discomfort to the surgeon — awkward stance and long procedure.

- Medical staff can assist patients remotely, or in transit [4].
- A robot can, in theory, operate more precisely and tirelessly than a human practitioner — eliminating the possibility of human-error.

Justification of the Statement

State of and Research Gaps in Robotic Assistance and Operation

✓ Effective motion compensation algorithms do exist.

- *Precision path-planning* needs significant improvement to operate on arteries and veins (2 to 4 mm in diameter) .
- Most robots function in a *purely manual mode*, with limited autonomy. The need for a neurosurgeon has **not** been eliminated yet.
- Development of thrombectomy robots is still in its early stages — most of them being primitive and largely manual.

■ Assistive robot with the ability to switch to telerobotic control in emergencies is proposed.

Definition

Motion Compensation Algorithms achieve cancellation of organ motion in the surgical field. Helps to maintain a steady pose with respect to the field by tracking its motion and moving along with it.

Feasibility Study

Feasibility Study

Datasets to validate stroke type differentiation

- *Proprietary* annotated series-CT data provided by *Chettinad Academy of Research and Education*.
- *Open-access* CT imaging data sets available for additional needs [5, 6, 7, 8].

Simulation Environments to test path-planning

- Need robust configurable environments for validating the path-planning algorithms.
- Such environments applicable to the medical domain exist: Assistive Gym [9], OpenAI Gym [10], Asynchronous Multi-Body Framework [11], Vinci Surgical System [12].
- The environments can be configured using the reconstructed CT and the compuational vascular model.

Feasibility Study

Computational structural models using CT

- Structural and mechanical properties of *pediatric femurs* were captured using a CT-based modeling approach in [13].
- Computational patient-specific vascular models were generated using MRIs of ischemic stroke, factoring geometry and hemodynamics in [14].
- A basic anatomical structure of the vascular structure at the site of study will be modeled based on standard parameters.
- The reconstructed CT can be used to translate specific anatomic and clot location information to produce personalized models [15].
- The computational model configures a robotic environment to validate the path-planning algorithm.

Feasibility Study

Path-planning for assistive autonomy

- Existing *motion compensation algorithms* will be effective in achieving pose stability.
- The state-of-the-art Trauma Pod (TP) performs critical acute stabilization and procedures [16].
- TP performs some autonomous tasks and precise operations — we intend to extend this for thrombectomy.
- Reliable switching between autonomous and teleoperative intervention has been implemented in [16, 4].
- Successful surgical procedures have been performed using robotic arms in precision environments [17, 18, 19, 20] — with effective path-planning, precision can be achieved in autonomous operation.

Architectural Design of the Proposed System

Proposed Clinical Workflow

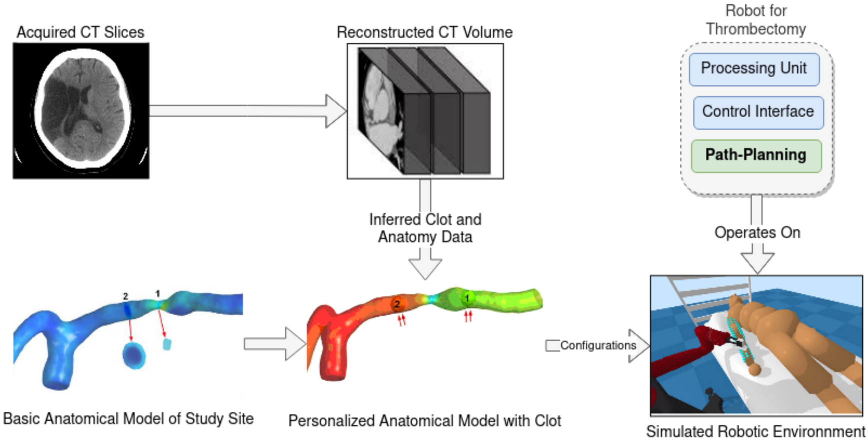
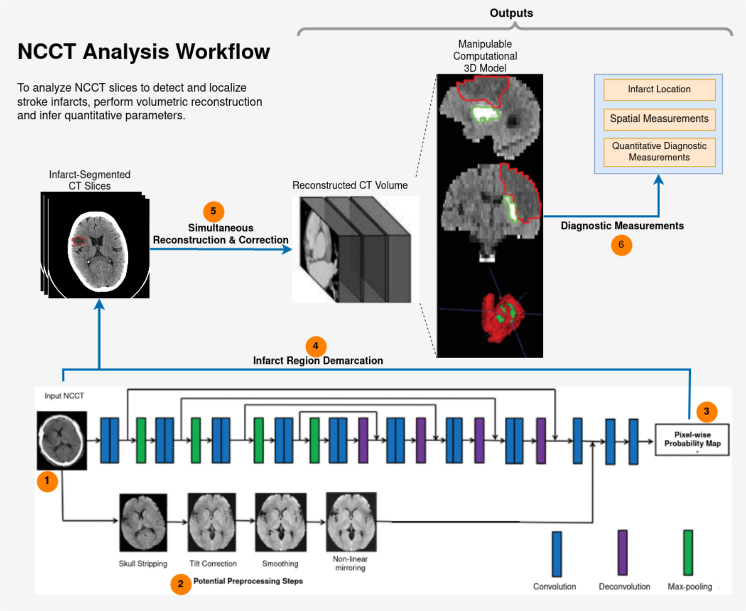


Figure: Proposed clinical workflow for Ischemic Stroke detection and treatment.

Objectives of the Workflow

- Detect the presence of and *differentiate between ischemic and hemorrhagic* infarcts from NCCT.
- Localize and *segment regions* representing normal and infarct regions.
- Reconstruct the volumetric NCCT from the slices while *simultaneously extrapolating and correcting* infarct segmentation.
- Infer *location and other quantitative diagnostic measures* from the reconstructed volumes to assess position and other parameters.
- Fuse patient-specific details to integrate the quantitative infarct measures with a *computational structural brain model*.
- Transfer the structural model parameters to a robotic *simulation environment* constructed using a '*robot visualization gym*'.
- Devise *path-planning strategy* for robot-assisted thrombectomy in the simulation environment with support for manual intervention.

NCCT Analysis for Infarct Classification and Localization



Expected Outcomes

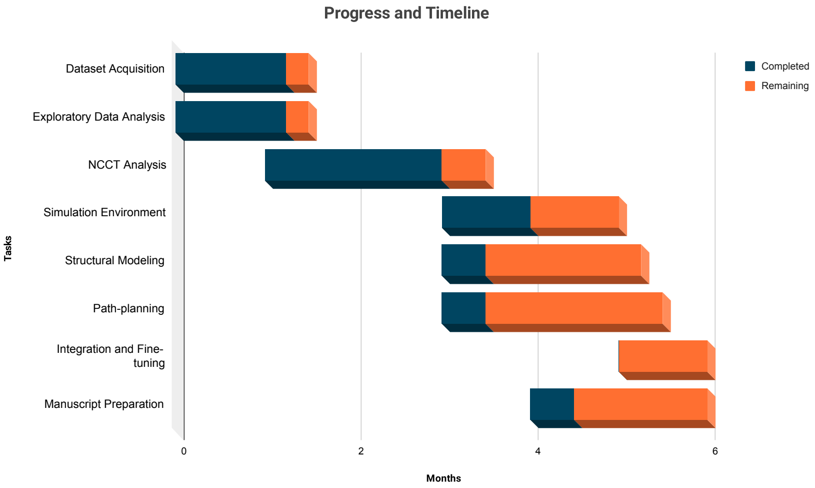
Expected Outcomes

In correlation with the proposed objectives, we aim to deliver the following **software elements** at the end of project term,

- *Algorithm* to 3D visualize, localize, and classify the stroke type from series-CT imaging.
- *Path-planning for a precision robot* that performs assistive thrombectomy autonomously, with the ability to switch to telerobotic control in critical situations.
- *Computational structural model* of a region of the brain that will be chosen based on statistical centrality of the patient samples.
- *CT-configurable robotic simulation environment* that translates the computational model to evaluate the path-planning algorithm.

Project Timeline

Tentative Timeline and Progress



Overview of Cumulative Progress

- ✓ Acquisition of *open-access datasets* for comparative method and model development.
- ✓ Preliminary *contact with radiologists* to acquire proprietary data.
- ✓ *Literature review* of current NCCT analysis techniques.
- ✓ *Exploratory data analysis* for pre-development statistics, data validation, and translatability analysis.
- ✓ Experiments and analysis of *stroke type classification* approaches.
- ✓ Experiments and analysis of *stroke infarct segmentation* and localization approaches – supervised and unsupervised.
- ✓ Extended literature review of computational models and robot simulation environments.

Datasets Chosen After EDA

- A *Brain Tumor Classification* dataset sourced from Kaggle comprising over 3,000 scan slices of the brain, classified into four tumor types.
- A peer-reviewed *Intracranial Hemorrhage Segmentation* dataset [21] comprising 2500 brain window images and 2500 bone window images collected from 82 patient samples.

Source Code

`https://github.com/karthik-d/Vision-For-Robot-Path-Planning`

Stroke Type Classification Approaches

Table: Comparison of classification approaches on open-access datasets.

Approach	Dataset	Accuracy
SVM	Open-Access Brain Tumor Dataset [Kaggle]	96.73%
Five-layer CNN		94.62%
ResNet-152		93.86%
GoogLeNet		85.13%
MobileNet		88.45%
EfficientNet-B0		**98.71%**
EfficientNet-B1		98.37%

Source Code

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Stroke Type Classification Approaches

Key Inferences

- The EfficientNet backbone, in general, offers the best performance.
- To accomodate for potential scarcity in labeling, this backbone can be extended to used other learning methods.
- Eg: The EfficientNet backbone can be applied as a backbone for Few-shot Learning to learn with minimal data.
- Eg: The EfficientNet backbone can be applied as an encoder architecture for semi-supervised and unsupervised techniques.
- The data characteristics analyzed through EDA make it translatable to the proprietary dataset we will acquire.

Source Code

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Stroke Infarct Segmentation Approaches

Table: Comparison of segmentation approaches on open-access datasets.

Approach	Backbone	Dataset	Accuracy	AuROC
FPN	DenseNet121	Licensed Open-Access Intracranial Hemorrhage Dataset [21]	95.19%	78.07%
FPN	**EffNet-B0**		**96.32%**	**95.60%**
FPN	ResNet-152		51.18%	78.20%
UNet	DenseNet121		89.94%	95.02%
UNet	**EffNet-B0**		**95.90%**	**94.70%**
UNet	ResNet-152		97.26%	66.01%
Clustering Analysis			**82.72%**	**82.09%**

Source Code

`https://github.com/karthik-d/Vision-For-Robot-Path-Planning`

Stroke Infarct Segmentation Approaches

Key Inferences

- The EfficientNet backbone, once again, offers the best performance.
- Both **spatial-pyramid pooling** and **encoder-decoder** architectures were tried for versatility.
- As a general trend, the encoder-decoder architecture appears more promising for adopting in low-annotation regimes.
- The **unsupervised clustering approach** is of particular value in low-annotation regimes. The backbones can be used as *autoencoders* for dimensionality reduction.
- Again, few-shot learning can be applied with this backbone to counter availability of segmentation masks.

Source Code

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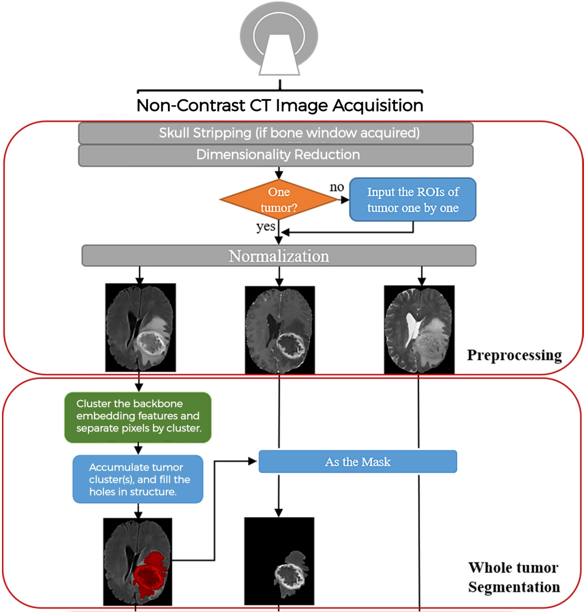
Unsupervised Stroke Infarct Segmentation



Extended Literature Review of Simulation Environments

- **OpenAI Gym** is a comprehensive collection of environments to train and test reinforcement learning algorithms. We particularly intend to use its "pusher" environment that simulates a robotic arm pushing an object towards a target position.
- **Panda Gym** [22] provides a set of RL environments integrated with the OpenAI Gym. It provisions five tasks, namely reach, push, slide, pick place, and stack.
- **Robo Gym** [23] is a unified setup for simulation and real environments, allowing seamless transfer from training to application. Particularly known for its distributive capabilities, it provides further scope for extension.

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Thank You