

# NeuroX Hybrid: Advanced Brain Analysis Platform

## Review I – Problem Identification, Domain Analysis & Feasibility Study

**Project ID/Code:** BCSE498J

**Team Members:**

- Munta Sai Karthik – 22BCE5060
- Gotam Sai Varshith – 22BCE1605
- Manideep Sandireddy – 22BCE1434

**Guide:** Dr. Jayaram B

**Department:** Computer Science and Engineering

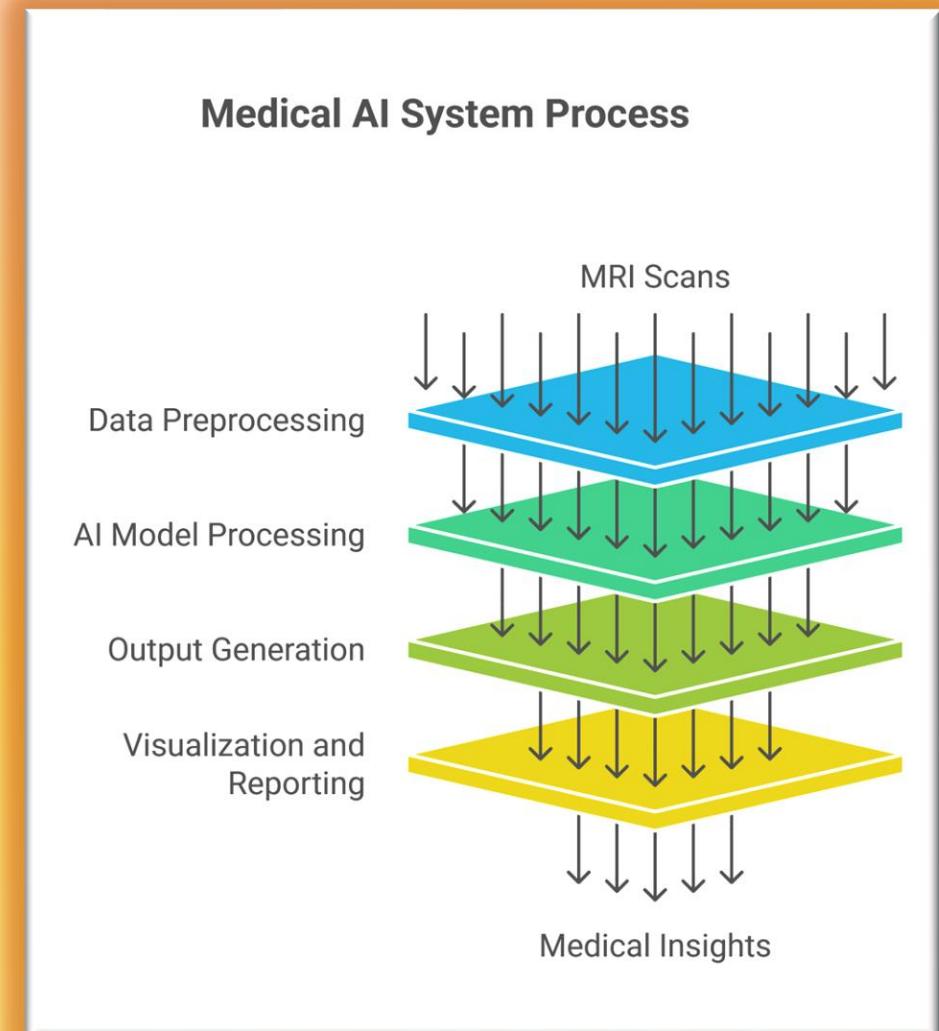


# Project Abstract

- **The Goal:** To design an automated "Hybrid" Deep Learning system for the simultaneous segmentation and classification of brain tumors from 3D MRI scans.
- **The Problem:** Manual MRI analysis is slow (1-3 hours/patient) and prone to human error. Standard AI models often fail to capture the "global context" of the brain.
- **The Solution:** A unified framework combining 3D ResNets (for detail) and Swin Transformers (for context).
- **Outcome:** A web-based dashboard delivering 3D interactive visualizations and AI-generated clinical reports.

# High-Level System Concept

- **Input:** Raw Multi-Modal MRI data (NIfTI format).
- **Processing Layers:**  
The image demonstrates our layered approach:  
Data Preprocessing → AI Model Inference → Output Generation.
- **Output:** The system transforms raw pixels into "Medical Insights" (Reports & 3D Models).



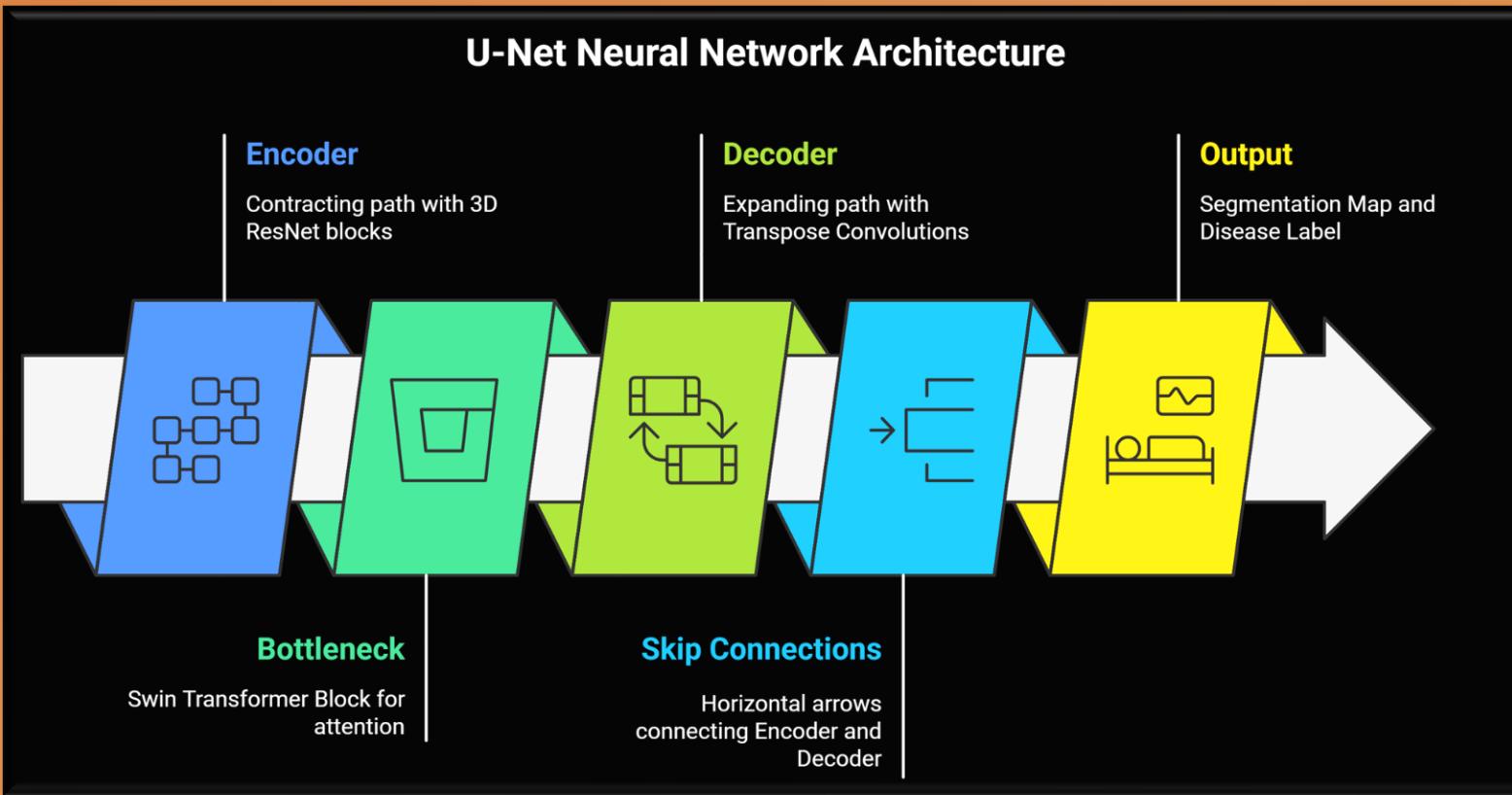
# Domain Identification (Rubric: Domain)

- **Primary Domain:** Medical Computer Vision.
- **Sub-Domain:** Volumetric (3D) Image Segmentation.
- **Clinical Context:**
  - **Neuroradiology:** We are addressing the diagnosis of Gliomas and Meningiomas.
  - **Multi-Modal Data:** The domain requires analyzing 4 MRI sequences (T1, T1ce, T2, FLAIR) simultaneously to distinguish edema from the tumor core.
- **Relevance:** Accurate segmentation is critical for radiotherapy planning and tracking tumor growth.

# Problem Identification (Rubric: Problem ID)

- **Bottleneck:** Radiologists face "Reader Fatigue." Manual segmentation is subjective; two doctors may trace the same tumor differently.
- **The "Context" Problem:**
  - Tumors have irregular shapes and fuzzy boundaries.
  - **Class Imbalance:** Healthy brain tissue vastly outnumbers tumor pixels, making it hard for standard models to find small lesions.
- **Technical Gap:** Existing tools are either fast but inaccurate (2D slices) or accurate but computationally impossible (Pure 3D Transformers).

# Background – The Standard Approach



- This image shows the U-Net architecture, the current industry standard.
- **Strengths:** Good at local feature extraction (edges/textures) using the "Encoder-Decoder" structure.
- **Weakness:** It lacks "Global Attention." It sees the tumor's edge but struggles to understand where the tumor is relative to the rest of the brain structure.

# Motivation for "Hybrid" Architecture

- **Why Hybrid?** We propose combining the best of two worlds:
  1. **CNN (ResNet):** Excellent at capturing high-frequency details (boundaries, texture).
  2. **Transformer (Swin):** Excellent at capturing long-range dependencies (relationships between distant pixels).
- **The Synergy:** The CNN handles the "what" (tumor texture), and the Transformer handles the "where" (spatial location).

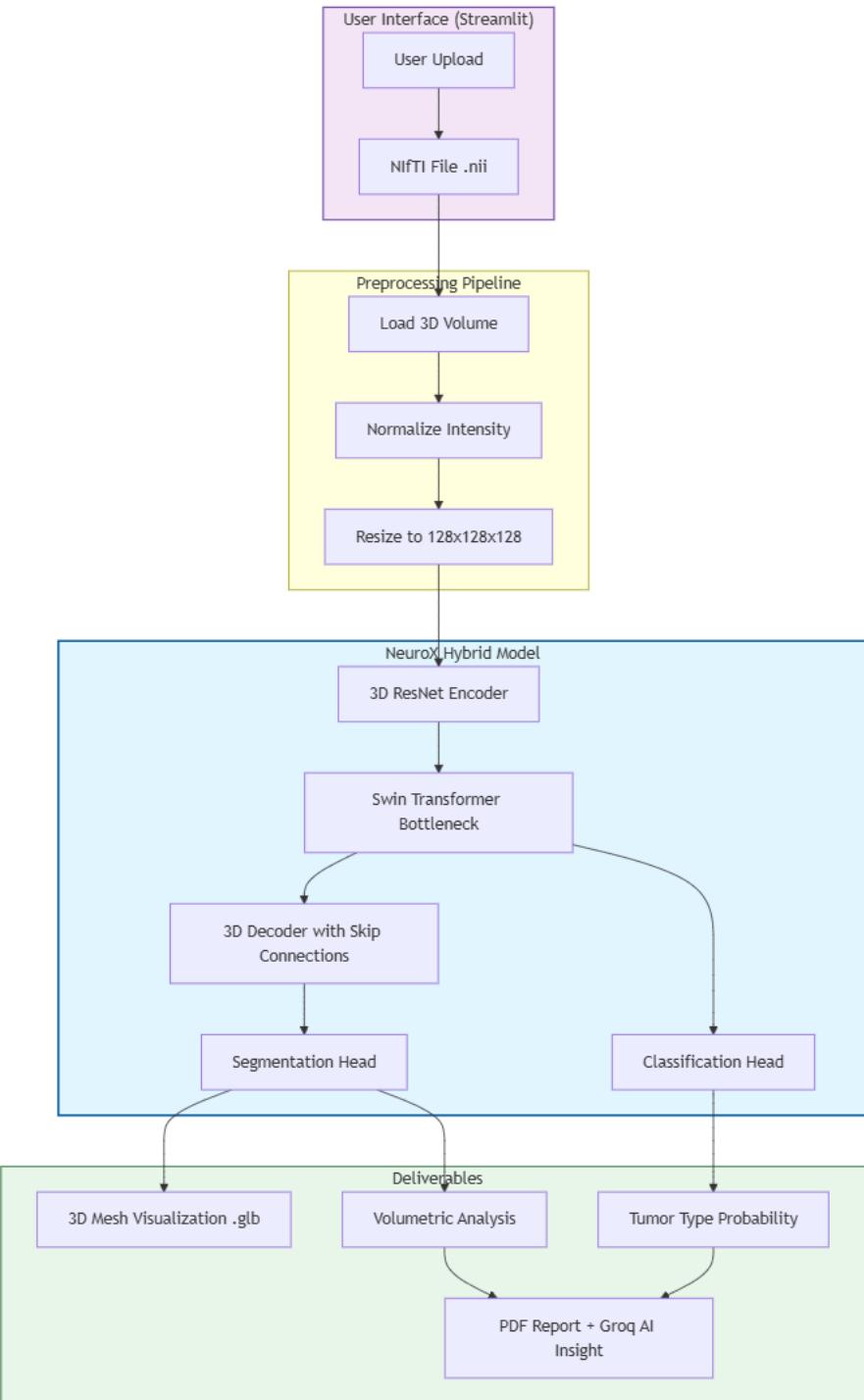


# Problem Statement

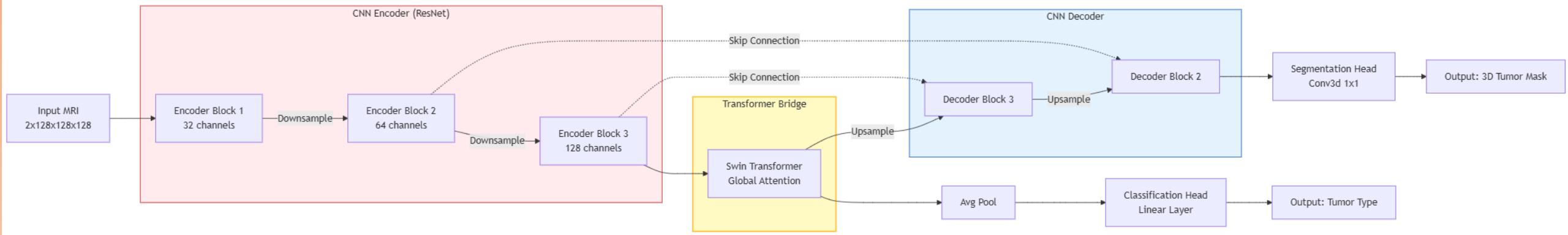
- **Statement:**
  - "To design and develop a Hybrid Deep Learning Framework that integrates 3D Residual Networks and Swin Transformers to automate the segmentation of brain tumor sub-regions and the classification of tumor types (Glioma, Meningioma, Pituitary) from multi-modal MRI scans."
- **Success Criteria:**
  - Dice Coefficient  $> 0.85$  for Whole Tumor.
  - Inference time  $< 60$  seconds per patient.

# System Workflow

- **Workflow Steps:**
  1. **User Input:** Upload .nii or .nii.gz file via Streamlit UI.
  2. **Preprocessing:**
    - Load 3D Volume.
    - Normalize Intensity (0-1 scale).
    - Resize to ROI (128, 128, 128).
  3. **NeuroX Inference:** The Hybrid model processes the data.
  4. **Deliverables:** 3D GLB Mesh generation + PDF Report creation.



# Proposed Architecture (Technical Core)



**Encoder (Pink):** Uses ResBlock3D to downsample features.

**Transformer Bridge (Yellow):** The key innovation. A SwinBlock3D processes the latent features with self-attention.

**Dual Heads (Purple):**

**Segmentation:** Outputting a 3D mask.

**Classification:** Outputting disease probability.

# Feasibility – The Encoder

- **Component:** ResBlock3D (Residual Block).
- **Function:** Extracts features using 3D Convolutions (nn.Conv3d) and Group Normalization (nn.GroupNorm).
- **Feasibility Check:** We limit the channel depth to  $32 \rightarrow 64 \rightarrow 128$  filters. This ensures the model fits within the VRAM of standard GPUs (e.g., T4 or RTX 3060).

# Feasibility – The Transformer Bridge

- **Component:** SwinBlock3D.
- **Mechanism:** Uses nn.MultiheadAttention to analyze relationships between features.
- **Optimization:** Instead of standard attention (which is  $O(N^2)$ ), we use window-based attention to reduce computational complexity, making 3D processing feasible.

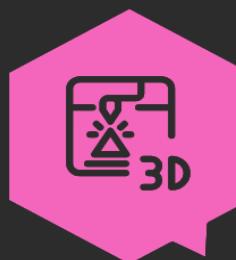
# Assumptions & Constraints

- **Assumptions:**
  - **Input Format:** Data must be in NIfTI format (standard for medical research).
  - **Modality:** Scans must contain at least two channels (e.g., FLAIR + T1ce) for accurate feature extraction.
- **Constraints:**
  - **Resolution:** Input is strictly cropped/resized to (128, 128, 128) to prevent Memory OOM errors.
  - **Scope:** Model detects only Glioma, Meningioma, and Pituitary tumors; it is not a general-purpose brain anomaly detector.

# Implementation Plan

## Visualization

Trimesh is used for 3D Mesh export.



## Reporting

ReportLab for PDF generation and Groq API for AI interpretation.



## Datasets

BraTS 2023 for Glioma segmentation, ISLES 2022 for stroke lesion robustness, and ADNI 3 for structural reference.

## Framework

PyTorch and MONAI are used as the framework.

# Conclusion & Future Work

- **Summary:** NeuroX Hybrid addresses the limitations of standard CNNs by integrating Transformers for better context.
- **Status:** Architecture is defined, datasets are identified, and the feasibility of 3D processing is confirmed via the  $128^3$  constraint.
- **Next Phase:** We will proceed to training the Encoder-Decoder on the BraTS dataset and developing the Streamlit frontend.