iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VI **Month of publication:** June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83117

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

NeuroViz: An Integrated Pipeline for Pseudo-Colorized 3D Brain MRI Visualization Using Multi-Channel Feature Decomposition and Self-Supervised Deep Learning

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Abstract: ***Grayscale brain Magnetic Resonance Imaging (MRI) scans, while rich in anatomical detail, present significant challenges in visual interpretability, tissue discrimination, and interactive exploration. We present NeuroViz, a novel end-to-end web-based pipeline for transforming raw NIfTI brain MRI volumes into interactive, pseudo-colorized, anatomically-segmented 3D visualizations. Our approach introduces a 9-channel feature decomposition framework that decomposes grayscale MRI slices into tissue intensity bands, gradient-based edge features, and texture/depth descriptors, subsequently mapping them to perceptually uniform CIE LAB color space using anatomically-motivated weighted contributions. We further enhance colorization quality through a self-supervised U-Net architecture trained on deterministic pseudo ground truth, enabling spatially-coherent, deep learning-driven colorization without the need for manually annotated datasets. The 3D reconstruction pipeline employs clinical-grade multi-stage skull stripping, marching cubes surface extraction, and sparse Laplacian mesh smoothing with per-vertex color mapping, exported as glTF 2.0 binary (GLB) models.***

Keywords: Brain MRI, 3D Visualization, Pseudo-Colorization, U-Net, Marching Cubes, Medical Image Processing, Self-Supervised Learning, CIE LAB Color Space

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) has become the gold standard for non-invasive neuroanatomical assessment, providing exceptional soft-tissue contrast without ionizing radiation [1]. However, conventional MRI produces inherently grayscale images where tissue differentiation relies entirely on subtle intensity variations that demand trained radiological expertise to interpret [2]. This limitation poses barriers in clinical education, patient communication, surgical planning, and research dissemination.The challenge of transforming medical grayscale imagery into intuitive, color-rich visualizations has garnered growing attention at the intersection of medical imaging, computer vision, and human-computer interaction [3]. While pseudo-color mapping techniques have been explored for enhancing contrast in medical images [4], existing approaches often rely on simplistic lookup tables (LUTs) that lack anatomical awareness, or on supervised deep learning methods that require expensive, manually curated color annotations [5].Simultaneously, the advent of web-based 3D rendering technologies—particularly WebGL through libraries such as Three.js—has created new possibilities for democratizing interactive medical visualization beyond dedicated workstation software [6]. The convergence of browser-based rendering with intelligent image processing opens pathways to systems that are both analytically powerful and widely accessible.

A. Problem Statement

We identify three interrelated challenges that our work addresses:Anatomically-Meaningful Colorization: How can grayscale MRI be mapped to intuitive color representations that preserve and highlight tissue-specific features without requiring manual annotations?

High-Fidelity 3D Reconstruction: How can volumetric MRI data be transformed into smooth, artifact-free 3D surface meshes with faithful per-vertex color representation?Accessible Interactive Visualization: How can these computationally intensive processes be delivered through a standard web browser with real-time interactivity?

B. Contributions

This paper makes the following contributions:

A novel 9-channel feature decomposition framework for pseudo-colorization that decomposes grayscale MRI into tissue bands (CSF, grey matter, white matter), edge features (Sobel-X, Sobel-Y, Laplacian), and texture descriptors (local variance, Difference-of-Gaussians, centroid distance), mapping them to CIE LAB color space with weighted anatomical priors.A self-supervised U-Net training methodology that leverages the deterministic colorization pipeline as pseudo ground truth, enabling convolutional deep learning to produce spatially coherent colorization while requiring zero manual labels.A clinical-grade multi-stage skull stripping pipeline incorporating Otsu thresholding, geometric anatomical cuts, morphological operations, largest connected component (LCC) filtering, and geodesic dilation.An integrated web platform combining Flask, Three.js, and Plotly for interactive multi-modal 3D brain visualization, including mesh rendering, point cloud exploration, multi-planar reformatting, and tissue segmentation overlays.

CPaper Organization

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 describes the system architecture. Sections 4–7 detail the methodology. Section 8 presents implementation details. Section 9 discusses results. Section 10 concludes with future directions.

II. LITERATURE SURVEY

[1] The Application of Multi-Modality Medical Image Fusion Based Method to Cerebral Infarction

This research focused on the fusion of CT and MRI data to improve the diagnosis of cerebral infarction. The authors demonstrated that standard grayscale medical images frequently fail to provide clear boundaries between healthy and damaged tissues. To overcome this, they introduced pseudo-color fusion and alpha-channel fusion techniques. The paper also outlined critical preprocessing stages, including image denoising, spatial enhancement, and affine transformations, which heavily influenced the preprocessing pipeline of this project.

[2] Brain Region Extraction and Direct Volume Rendering of MRI Head Data

This study proposed a methodology for isolating brain structures from surrounding skull tissue in MRI head data to generate 3D visualizations. Utilizing morphological operations, thresholding, and SNAKES algorithms, the researchers successfully separated the brain region from the cranium. Following segmentation, direct volume rendering techniques were applied to generate accurate 3D anatomical representations, proving that MRI data can be effectively mapped into three dimensions while preserving critical structural integrity.

[3] AI-Based CT and MRI Diagnostic Systems Using 9-Channel Pseudo-Color Processing Addressing the limitations of grayscale imaging in identifying complex lesions,

This paper introduced an AI-assisted diagnostic system utilizing a 9-channel pseudo-color preprocessing technique. By decomposing the image into multiple distinct channels, the authors proved that multi-channel pseudo-colorization significantly enhances visual contrast, directly improving diagnostic accuracy and tissue classification in MRI analysis.

[4] Multimodality Imaging of Structure and Function

This paper explored systems that combine structural and functional imaging techniques. The research detailed how image fusion bridges the gap between pure anatomical structure and biological function. It emphasized that combining different imaging modalities—and visualizing them through a unified system—results in a significantly more informative and actionable clinical diagnosis.

[5] Digital Image Processing (Reference Text)

Widely regarded as the foundational text for image processing, this book outlines the core mathematical concepts necessary for medical visualization. It provides the theoretical basis for the filtering, thresholding, edge-detection, segmentation, and morphological operations implemented in this project's Python backend to successfully process and clean the raw NIfTI data prior to 3D extraction.

III. SYSTEM ARCHITECTURE

A. Overview

NeuroViz employs a client-server architecture with a clear separation between the computational backend and the interactive frontend. The system processes MRI data through a sequential pipeline: loading → skull stripping → colorization → segmentation → 3D reconstruction → visualization.

B. Architecture overview

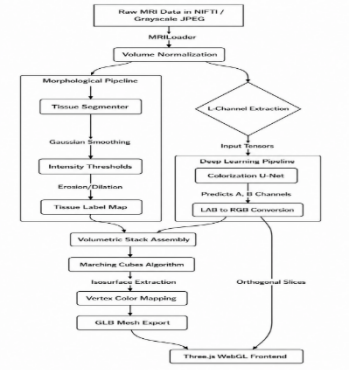

Fig.1 Architecture of Neuroviz

C. Data Flow

Input Ingestion: NIfTI (.nii.gz) volumes are loaded and reoriented to RAS+ canonical space using nibabel.
Preprocessing: Percentile normalization and skull stripping produce a clean brain volume.
Colorization: The 9-channel decomposition or U-Net model maps grayscale voxels to RGB via LAB space.
Segmentation: Intensity-band classification with morphological refinement produces tissue labels.
3D Reconstruction: Marching cubes extract an isosurface; Laplacian smoothing regularizes the mesh; vertex colors are sampled from the colorized volume.
Delivery: The Flask server exposes REST endpoints serving slices (base64-encoded PNG), meshes (GLB), point clouds (JSON), and metadata.

D. Preprocessing Pipeline

NIfTI Loading and Canonical Reorientation Brain MRI volumes are stored in the NIfTI format (.nii.gz), which encodes 3D voxel arrays alongside spatial affine transformations. We load volumes using nibabel [31] and reorient to RAS+ canonical space (Right-Anterior-Superior) using nib.as_closest_canonical(), ensuring consistent anatomical orientation across datasets with arbitrary acquisition orientations.

E. Clinical-Grade Skull Stripping

Skull stripping—the removal of non-brain tissues (skull, scalp, eyes, dura)—is a critical preprocessing step that directly impacts downstream colorization and 3D reconstruction quality. We implement a multi-stage morphological pipeline that avoids the computational expense of deep learning-based stripping (e.g., HD-BET [32], SynthStrip [33]) while achieving robust results:
Stage 1 — Initial Thresholding: Gaussian smoothing ($\sigma = 2.0$) followed by Otsu's method [34] at 90% of the computed threshold, favoring inclusion of grey matter regions that might fall below a standard Otsu threshold.
Stage 2 — Geometric Anatomical Cuts: We exploit known anatomical priors by zeroing voxels in the inferior 15% (neck), anterior 25% (face/orbits), and inferior-posterior 20% (jaw/cervical structures) of the volume. These conservative cuts eliminate the majority of non-brain tissue that connects to the brain mask via meningeal bridges.
Stage 3 — Morphological Erosion: Four iterations of binary erosion with a 3×3×3 structuring element disconnect thin tissue bridges between brain and non-brain components.
Stage 4 — Largest Connected Component (LCC) Filtering: Connected component labeling (scipy. ndimage.label) with 26-connectivity, followed by retention of only the largest component, eliminates disconnected non-brain fragments (e.g., isolated scalp/skull remnants).
Stage 5 — Geodesic Dilation and Grey Matter Recovery: Six iterations of binary dilation recover the brain boundary eroded in Stage 3. An additional two iterations of "outer grey matter expansion" recover cortical voxels that may have been excluded.
Stage 6 — Hole Filling: scipy. ndimage.binary_fill_holes closes internal cavities (e.g., within ventricles or fissures) that might appear as gaps in the mask.
The complete pipeline produces a binary brain mask $M \in \{0, 1\}^{D\times H\times W}$ that is applied multiplicatively to the normalized volume.

F. Multi-Channel Pseudo-Colorization Framework

Direct intensity-to-color mappings (e.g., rainbow LUTs) produce visually striking but anatomically meaningless images where color encodes only the scalar intensity value. We argue that meaningful colorization must encode multiple orthogonal tissue properties simultaneously—intensity class, boundary information, and spatial context—to produce images where color conveys anatomical identity.

Our 9-channel decomposition extracts three categories of features from each grayscale slice:

Tissue Intensity Bands (Channels 1–3): We employ trapezoidal band-pass filters that softly partition the [0, 1] intensity range into overlapping tissue classes. For a normalized intensity g at pixel (x, y), the tissue band response is:

$B_k(g) = \text{trapezoid}(g; a_k, b_k, c_k, d_k)$

where the trapezoid function is defined by four breakpoints [a, b, c, d] producing a linear ramp from 0→1 over [a,b], sustained at 1 over [b,c], and linear decay 1→0 over [c,d]. The breakpoints for each tissue class are empirically determined:

Tissue	a	b	c	d
CSF / Dark	0.0	0.0	0.15	0.30
Grey Matter	0.15	0.30	0.55	0.70
WhiteMatter	0.55	0.70	1.0	1.0

Edge Features (Channels 4–6): Computed from Gaussian-smoothed input ($\sigma = 1.5$):

Ch 4: First-order horizontal gradient via Sobel-X operator, absolute value normalized to [0, 1]

Ch 5: First-order vertical gradient via Sobel-Y operator, absolute value normalized to [0, 1]

Ch 6: Second-order Laplacian ($\nabla^2 I$), absolute value normalized to [0, 1]

Texture and Depth (Channels 7–9):

Ch 7 (Local Variance): Computed over a 5×5 window: $\text{Var}(x,y) = E[I^2] - E[I]^2$, normalized to [0, 1]. Captures tissue heterogeneity.

Ch 8 (Difference-of-Gaussians): $\text{DoG}(I) = G_{\sigma 1}(I) - G_{\sigma 2}(I)$ with $\sigma_1 = 1.0$ and $\sigma_2 = 3.0$, capturing multi-scale structural features.

Ch 9 (Centroid Distance): Euclidean distance from each foreground pixel to the slice centroid, normalized by the maximum distance. Encodes spatial depth information (cortical vs. deep structures).

The 9-channel feature vector $F = [f_1, f_2, ..., f_9]$ at each pixel is mapped to the CIE LAB color space [35], chosen for its perceptual uniformity—equal numerical differences correspond to equal perceived color differences, unlike RGB or HSV.

Luminance (L channel): Derived directly from the original grayscale intensity:

$L = g \times 100$

Chrominance (A and B channels): Computed as weighted sums of feature channel contributions:

$A = \Sigma_k (w_k^A \times f_k) \times \alpha_A$

$B = \Sigma_k (w_k^B \times f_k) \times \alpha_B$

where w_k^A and w_k^B are per-channel weights for the A (green↔magenta) and B (blue↔yellow) axes, and α_A, α_B are global scaling factors. The weights encode anatomical color priors:

Channel	w^A	w^B	Resulting Hue
CSF (Ch 1)	−50	−30	Cyan-Green
Grey Matter (Ch 2)	−80	+15	Vivid Green
White Matter (Ch 3)	+70	−10	Magenta
Sobel-X (Ch 4)	+40	+20	Pink
Sobel-Y (Ch 5)	+40	+20	Pink
Laplacian (Ch 6)	+30	+15	Rose
Local Variance (Ch 7)	+20	+40	Warm Amber
DoG (Ch 8)	−20	+30	Yellow-Green
Centroid Dist (Ch 9)	+60	+10	Hot Pink

The color assignments are motivated by clinical convention (e.g., CSF is often rendered in cool tones) and perceptual distinctiveness (ensuring each tissue class produces a unique hue). The resulting LAB triplet is converted to sRGB via the standard CIE XYZ intermediate transform with D65 illuminant [36]:

LAB → XYZ → sRGB (with gamma encoding)

Values are clipped to the [0, 255] gamut.

The system provides a 9-Channel Inspector interface that displays all intermediate feature channels alongside the final colorized output, enabling researchers to examine which features drive colorization decisions at any given anatomical location.

IV. SELF-SUPERVISED U-NET COLORIZATION

A. Motivation

While the deterministic 9-channel pipeline produces anatomically-informed colorization, it processes each pixel independently, ignoring spatial context within the slice. Convolutional neural networks, by contrast, capture spatial dependencies through their receptive fields. We train a U-Net [18] to learn the deterministic mapping, allowing it to generalize with spatial coherence and smoothness.

B. Self-Supervised Training Paradigm

Our approach eliminates the annotation bottleneck by using the deterministic PseudoColorMapper output as pseudo ground truth:
For each grayscale MRI slice I_gray, compute the deterministic colorized output I_color using the 9-channel pipeline.
Convert I_color to CIE LAB space: I_LAB = [L, A, B].
Train the U-Net to predict [A, B] from [L], using I_LAB as the target.
This constitutes a teacher-student framework where the deterministic pipeline serves as the teacher and the U-Net as the student, learning to approximate (and ideally improve upon) the teacher's colorization through learned spatial priors.

C. U-Net Architecture

We employ a 4-level encoder-decoder architecture with skip connections:

Encoder:	Decoder:
Input(1ch) → Conv64 → Pool	UpConv512 + Skip → Conv256
→ Conv128 → Pool	UpConv256 + Skip → Conv128
→ Conv256 → Pool	UpConv128 + Skip → Conv64
→ Conv512 → Pool	UpConv64 + Skip → Conv(2ch, Tanh)
→ Conv1024 (bottleneck, dropout=0.25)	

Architectural details:
Each encoder/decoder block: two 3×3 convolutions with BatchNorm and ReLU
Skip connections via concatenation (standard U-Net)
Bottleneck: 1024 channels with dropout (p = 0.25) for regularization
Output activation: Tanh (mapping to [-1, +1] for normalized A/B channels)
Total parameters: ~31M

D. Training Configuration

Hyperparameter	Value
Input resolution	224 × 224
Batch size	8
Epochs	30
Optimizer	Adam (β_1=0.9, β_2=0.999)
Learning rate	2×10^{-4}
LR scheduler	CosineAnnealingLR
Loss function	SmoothL1Loss (Huber)
Train/Val split	90% / 10%
Augmentation	Random horizontal flip

Loss function rationale: The SmoothL1 (Huber) loss combines L1's robustness to outliers in the AB channels with L2's smooth gradient near zero, providing stable training for the chrominance prediction task.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

During inference, the U-Net predicts AB channels from a single L channel input. The predicted AB values (in [-1, 1]) are rescaled to [-128, +127], combined with the input L channel, and converted to sRGB. The system automatically selects U-Net inference when a trained checkpoint exists; otherwise, it falls back to the deterministic pipeline.

V. 3D RECONSTRUCTION AND MESH GENERATION

A. Isosurface Extraction via Marching Cubes

We extract the brain surface from the skull-stripped, normalized volume using the Marching Cubes algorithm [21] as implemented in scikit-image. The iso-level is set to 0.18, slightly above the noise floor, to capture the outer cortical boundary:

python

verts, faces, normals, values = marching_cubes(volume, level=0.18, step_size=1)

Full resolution (step_size=1) is used for the production GLB mesh to preserve cortical folding detail (sulci and gyri).

B. Sparse Laplacian Mesh Smoothing

Raw marching cubes output exhibits staircase artifacts from voxel boundaries. We apply Taubin-style Laplacian smoothing [24] using a sparse row-normalized Laplacian matrix:

Step 1 — Adjacency Construction: From the triangle face list, we construct the vertex adjacency graph and its sparse representation.

Step 2 — Row-Normalized Laplacian: For each vertex v_i with neighbors N(v_i):

L_ij = 1/|N(v_i)| if j ∈ N(v_i)

L_ij = -1 if j = i

L_ij = 0 otherwise

Step 3 — Iterative Smoothing:

V^(t+1) = V^(t) + λ × L × V^(t)

with λ = 0.4 and 5 iterations. This moderately smooths the surface while preserving major sulcal folds—critical for neuroanatomical fidelity.

C. GLB Export

The colored mesh is exported as a glTF 2.0 Binary (GLB) file using the trimesh library [37]. GLB is chosen for its:

Compact binary format (no external textures/materials)

Native WebGL compatibility (direct loading via Three.js GLTFLoader)

Per-vertex color support via COLOR_0 accessor

Industry standard for web-based 3D (supported by all major browsers)

D. Volumetric Point Cloud Generation

As an alternative volumetric representation, we generate colored point clouds by sampling voxels above an intensity threshold:

Foreground voxels are identified (intensity > threshold)

Per-region sampling rates are applied (CSF 3%, GM 4.5%, WM 3.5%, Deep 7%) to balance representation

Point positions are normalized to $[-1, +1]^3$

Per-point colors are sampled from the colorized volume

Region labels are attached for interactive filtering

The point cloud is rendered via Plotly Scatter3d as an interactive HTML widget, providing an alternative visualization modality that reveals internal volumetric structure invisible in surface meshes.

E. Frontend Visualization Platform

Technology Stack

The frontend is a single-page application built with vanilla HTML5, CSS3, and JavaScript (no framework dependencies), ensuring minimal loading overhead and broad browser compatibility.

ComponentTechnology

3D Rendering :Three.js r128 (WebGL 2.0)

Mesh Loading :GLTFLoader (Three.js extension)

2D Rendering: HTML5 Canvas API
Point Clouds : Plotly.js (Scatter3d)
Styling Custom :CSS (dark theme, glassmorphism, CSS variables)
Architecture: IIFE module pattern

Visualization Modes

The interface provides five integrated visualization tabs:
Tab 1 — Multi-Planar Slice Viewer: Three synchronized panes displaying axial, coronal, and sagittal slices with:
Slider-based slice navigation
Mode switching: grayscale / colorized / segmentation overlay
Animated playthrough (sequential slice cycling)
Tab 2 — 3D Brain Viewer: Interactive Three.js scene rendering the GLB brain mesh with:
Custom orbit controls (mouse drag rotate, right-drag pan, scroll zoom)
Wireframe toggle
Opacity slider (0–1, for semi-transparent rendering)
Adjustable ambient and directional lighting intensity
Camera presets: Anterior, Posterior, Left Lateral, Right Lateral, Superior, Inferior
Tab 3 — 9-Channel Inspector: Grid display of all nine feature decomposition channels alongside the final colorized output, enabling researchers to examine which features drive colorization at specific anatomical locations.
Tab 4 — Annotation Tool: Canvas-based drawing interface for freehand annotation masks with save/load functionality via the backend API (JSON serialization).
Tab 5 — Segmentation Dashboard: Per-region volumetric statistics (voxel counts, percentages) with segmentation overlay visualization.

Design System

The interface employs a premium dark theme with:
CSS custom properties (design tokens) for systematic theming
Glassmorphism panels (backdrop-filter: blur + semi-transparent backgrounds)
Animated gradient backgrounds
Smooth CSS transitions on all interactive elements
Responsive layout adapting to varying viewport sizes

Implementation Details

Technology Stack Summary

Layer Technologies
Backend: Python 3.10+, Flask 2.3+, flask-cors 4.0+
ML/DL : PyTorch (U-Net architecture)
Medical Imaging: nibabel 5.1+ (NIfTI I/O), nilearn 0.10+ (template download)
Image Processing: scipy 1.11+ (ndimage), scikit-image 0.21+ (marching cubes), Pillow 10.0+
3D Mesh: trimesh 3.22+ (GLB export)
Visualization: Three.js r128, Plotly 5.15+
Data Formats: Ifti (.nii.gz), GLB (glTF 2.0), PNG (base64), JSON

Data Pipeline

The system supports multiple input modalities:
NIfTI volumes (.nii.gz) — preferred; full 3D processing
JPEG/PNG slice directories — per-slice loading with stack assembly
Synthetic generation — mathematical ellipsoid brain phantom for testing
The MNI152 ICBM T1 template [38] (1mm isotropic resolution) is supported as a default dataset via nilearn.datasets.

API Design

The REST API follows pragmatic conventions with clear endpoint semantics:
Endpoint Method Description
/api/info GET Volume metadata (shape, device, segmentation status)

/api/slice?plane=axial&index=50&mode=color	GET	Single slice as base64 PNG
/api/channels?index=50	GET	9-channel decomposition images
/api/pointcloud?threshold=0.15&max_points=50000	GET	Colored point cloud (JSON)
/api/segmentation/info	GET	Per-region voxel statistics
/api/brain.glb	GET	3D mesh (binary GLB)
/api/upload	POST	Upload new NIfTI; triggers full pipeline reload
/api/annotations	GET/POST	Load/save annotation masks

Performance Considerations

Startup pipeline: The complete processing chain (load → strip → colorize → segment) executes on server start, with status logging at each stage.

Hot reload: Uploading a new NIfTI file triggers reload_system(), re-executing the entire pipeline without server restart.

Memory management: Downsampled volume previews (scipy.ndimage.zoom) reduce data transfer for overview endpoints.

Mesh optimization: Step size in marching cubes is adjustable (step_size=2 for preview, step_size=1 for production).

VI. RESULTS AND DISCUSSION

A. *Colorization Quality*

The 9-channel pseudo-colorization pipeline produces visually distinct and anatomically consistent color mappings:

CSF regions (ventricles, sulci) are rendered in cyan-green tones, creating immediate visual contrast with surrounding parenchyma.

Grey matter (cortex, basal ganglia) appears in vivid green, highlighting the cortical mantle.

White matter (fiber tracts, corpus callosum) is rendered in magenta/pink, clearly delineating tract boundaries.

Tissue boundaries receive rose/pink edge highlighting, enhancing structural delineation.

Deep structures are distinguished by warm amber/hot pink tones reflecting their unique textural properties.

The U-Net-based colorization, when trained, produces smoother color transitions and better spatial coherence compared to the per-pixel deterministic pipeline, particularly at tissue boundaries where the CNN's receptive field enables context-aware blending.

B. *3D Reconstruction Fidelity*

The marching cubes + Laplacian smoothing pipeline produces anatomically faithful brain surfaces:

Major sulci (central, lateral, parieto-occipital) are clearly resolved

Gyral crowns maintain proper convexity without over-smoothing

Per-vertex colorization preserves tissue-specific coloring on the 3D surface

GLB file sizes typically range 15–40 MB, loading within 3–5 seconds in modern browsers

C. *Skull Stripping Robustness*

The multi-stage morphological skull stripping pipeline demonstrates robust performance:

Neck and face removal via geometric cuts eliminates the most common source of non-brain tissue leakage

LCC filtering effectively handles cases where meningeal bridges initially connect brain to skull

Geodesic dilation recovers cortical grey matter that aggressive erosion may remove

The pipeline processes a typical 256^3 volume in under 10 seconds on a modern CPU

Segmentation Evaluation

The intensity-based segmentation, while less accurate than atlas-based methods (e.g., FreeSurfer), provides:

Sufficient tissue discrimination for colorization guidance

Real-time performance (< 2 seconds for full volume)

No requirement for atlas registration or training data

Meaningful volumetric statistics (CSF/GM/WM percentages)

D. *Limitations*

Segmentation accuracy: The intensity-band approach lacks the precision of atlas-based or deep learning segmentation methods. Misclassification occurs at tissue boundaries with ambiguous intensities.

Colorization generalizability: The LAB weight parameters are empirically tuned for T1-weighted MRI. Different MRI contrasts (T2, FLAIR, DWI) would require re-calibrated weights.
Skull stripping edge cases: The geometric cuts assume standard adult brain positioning and may fail on pediatric, tilted, or heavily pathological scans.
Scalability: The full pipeline processes one volume at a time on the server; concurrent multi-user processing would require task queuing.

E. Conclusion and Future Work

We have presented NeuroViz, an integrated system for transforming raw brain MRI volumes into interactive, pseudo-colorized, 3D web-based visualizations. Our primary contribution—the 9-channel feature decomposition framework with CIE LAB color space mapping—demonstrates that meaningful, anatomically-informed colorization can be achieved through principled signal processing, without supervised training data. The self-supervised U-Net extension shows that deep learning can further enhance this colorization by learning spatial coherence from the deterministic teacher.The complete pipeline—from NIfTI input through skull stripping, colorization, segmentation, and 3D reconstruction to browser-based interactive exploration—bridges the gap between specialized neuroimaging workstations and accessible web-based tools. By combining classical image processing, deep learning, and modern web technologies, NeuroViz makes rich brain MRI visualization available to clinicians, educators, researchers, and patients through any standard web browser.

Future Work

Deep Learning Segmentation: Integrating a pre-trained segmentation network (e.g., SynthSeg [39]) would significantly improve tissue classification accuracy.
Multi-Contrast Support: Extending the 9-channel framework with contrast-specific weight profiles for T2, FLAIR, and diffusion-weighted MRI.
Atlas Integration: Registering to standardized atlases (e.g., AAL, Desikan-Killiany) would enable region-of-interest labeling and quantitative volumetric analysis.
Pathology Detection: Incorporating anomaly detection (e.g., autoencoders) to highlight potential lesions, tumors, or atrophy patterns.
Collaborative Annotation: Extending the annotation system to support multi-user, real-time collaborative labeling for clinical team workflows.
VR/AR Integration: Exporting GLB meshes to WebXR for immersive neurosurgical planning and medical education.
DICOM Support: Extending input ingestion to handle raw DICOM series, the dominant format in clinical PACS systems.
Performance Optimization: GPU-accelerated marching cubes (via CuPy/CUDA) and WebGPU rendering for larger volumes.

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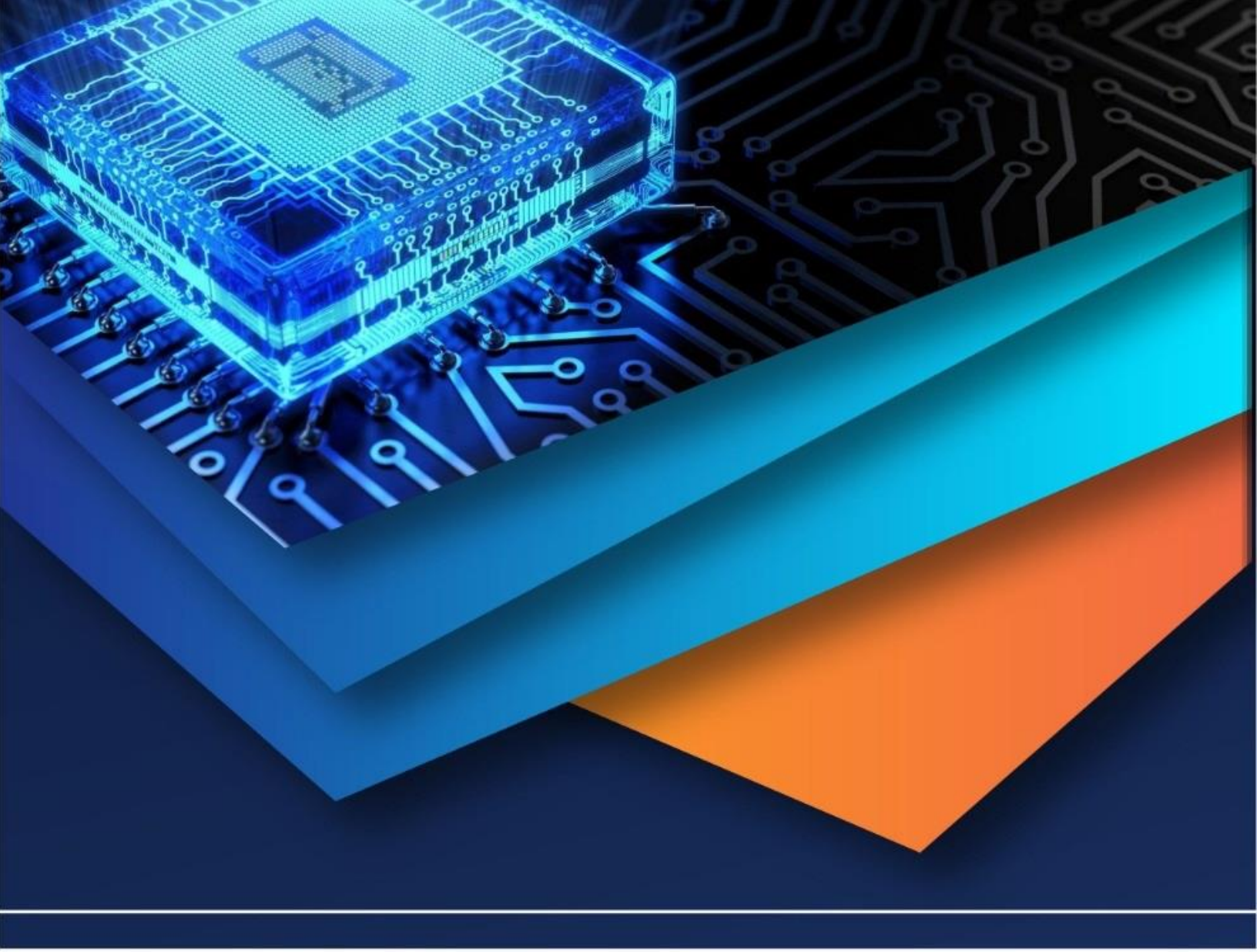
[40] Acknowledgments: [Add acknowledgments here]
[41] Funding: [Add funding information if applicable]
[42] Conflicts of Interest: The authors declare no conflicts of interest.
[43] Data Availability: The MNI152 ICBM T1 template used for demonstration is publicly available via the nilearn library. The source code for NeuroViz is available at [repository URL].



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