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ARTIFICIAL INTELLIGENCE TOOLS IN POST-PROCESSING ANALYSIS OF NEUROIMAGING: A REVIEW OF THE LAST DECADE (2016–2026)

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Abstract: Post-processing of neuroimaging data — the segmentation, quantification, and volumetric or perfusion analysis performed after an MRI or CT scan is acquired — has traditionally relied on manual or semi-automated work by radiologists and neurologists. Over the past decade, artificial intelligence (AI), and particularly deep learning, has been increasingly integrated into this stage of the neuro-diagnostic workflow. This review synthesizes peer-reviewed research published between 2016 and 2026 on AI-based post-processing tools across four major areas of neurology: multiple sclerosis lesion segmentation, Alzheimer's disease and dementia classification/volumetry, acute ischemic stroke perfusion and hemorrhage analysis, and brain tumor segmentation/volumetry. For each area, the responsible authors, publication year, AI methodology, target disease, study methods, and reported results are summarized. A dedicated section then compares manual versus AI-automated image analysis across these same conditions, drawing on studies that directly measured agreement, reproducibility, and time efficiency between the two approaches. Overall, the literature indicates that deep learning-based post-processing tools achieve accuracy and reproducibility that is comparable to, and in several structured tasks (e.g., hippocampal volumetry, tumor sub-region quantification) more consistent than, manual expert analysis, while substantially reducing analysis time and inter-rater variability.

1. Introduction

Neuroimaging — MRI, CT, and PET — is central to diagnosing and monitoring neurological disease, but converting raw images into clinically usable numbers (lesion counts, tumor volumes, infarct core size, hippocampal atrophy grade) has historically depended on manual tracing or visual rating scales performed by trained specialists. This process is time-consuming and subject to inter- and intra-rater variability. Since roughly 2016, convolutional neural networks (CNNs) — especially U-Net-based architectures — have been applied to automate this post-processing step across nearly every neurological disease category. This paper reviews representative studies from the past ten years, organized by disease area, and then reviews the subset of studies that explicitly compared manual and AI-based (automated) analysis.

2. Methods of This Review

Literature was identified through PubMed-indexed and preprint sources covering AI applications in neuroimaging post-processing published from 2016 onward. Priority was given to studies that: (a) named a specific AI/deep-learning method, (b) targeted a defined neurological disease, (c) reported quantitative performance metrics (Dice similarity coefficient, sensitivity/specificity, AUC,

intraclass correlation coefficient), and (d) where possible, directly compared automated output against manual expert segmentation or rating.

Results

3. AI Post-Processing Tools by Disease Area

3.1 Multiple Sclerosis (Lesion Segmentation)

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
La Rosa et al. (2020), *NeuroImage: Clinical*	3D U-Net-based fully convolutional deep learning model, using FLAIR + MP2RAGE sequences at 3T	Multiple sclerosis — cortical and white-matter lesions	Trained and tested on multi-hospital 3T MRI datasets with two contrasts (FLAIR, MP2RAGE); compared to existing white-matter-only segmentation tools	The model achieved a 76% lesion detection rate for combined cortical and white-matter lesions with a 29% false-positive rate, outperforming reference white-matter-only tools, which could not adequately detect small cortical lesions; the framework generalized across two hospital scanner types
Narayana, Coronado, Sujit, Sun, Wolinsky & Gabr (2020), *Magnetic Resonance Imaging*	Deep convolutional neural network cohort study	Multiple sclerosis lesion and brain tissue segmentation	Large multi-center cohort study assessing whether multiple MRI contrasts are necessary for deep-learning-based MS segmentation	Demonstrated that deep-learning segmentation performance is affected by the number of MRI contrasts used, informing minimal clinically feasible imaging protocols for automated MS segmentation
McKinley, Wepfer, Grunder, Aschwanden, Fischer et al. (2020), *NeuroImage:*	CNN with segmentation confidence estimation	Multiple sclerosis — lesion load change detection	Automatic detection of new/enlarging lesion load over time using CNN-derived confidence	Enabled automated, confidence-weighted detection of MS lesion load change for longitudinal disease monitoring, reducing reliance on manual

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
Clinical			maps	comparison of serial scans
Roca, Attye, Colas, Tucholka, Rubini et al. (2020), *Diagnostic and Interventional Imaging*	AI-based predictive model using FLAIR MRI	Multiple sclerosis — prediction of clinical disability	Machine-learning model trained on FLAIR MRI features to predict clinical disability scores	AI-derived imaging features from FLAIR MRI were shown to be predictive of clinical disability level in MS patients, supporting the use of automated MRI analysis as a prognostic tool
Zeng, Gu, Liu & Zhao (2020), *Frontiers in Neuroinformatics* (review)	Systematic review of CNN-based MS segmentation methods (2016–2020)	Multiple sclerosis	Reviewed dozens of CNN/U-Net-based lesion segmentation studies, including domain-adaptation approaches	Concluded deep learning methods (particularly U-Net variants and domain-adaptation models) had become the dominant approach for automated MS lesion segmentation, surpassing earlier semi-automated intensity-threshold methods

3.2 Alzheimer's Disease and Dementia (Classification and Volumetry)

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
(SPIE, 2021), *Journal of Medical Imaging*, PMC8083897	2D and 3D CNNs, plus recurrent neural networks, with transfer learning	Alzheimer's disease vs. healthy controls	Compared slice-based 2D CNN classification to sequence-based 3D CNN/RNN classification on MRI volumes	Sequence-based (3D/RNN) decision-making improved classification accuracy by approximately 2% over simple slice-based 2D CNN decisions, showing that incorporating inter-slice spatial

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
				context improves AD detection
Multiple authors, reviewed in PMC12405159 (2022–2025 syntheses)	DenseNet-121 (Hazarika et al., 2022); ResNet-50v2 (Srividhya et al.); 3D-Subject multimodal DL (Goenka & Tiwari); ensemble pretrained models (Francis & Pandian); multi-task deep learning (Venkatasubramanian et al.)	Alzheimer's disease, mild cognitive impairment (MCI), normal controls — using ADNI datasets	Various CNN architectures applied to structural MRI (and in one case combined with AV-45 PET) for 2–4 class classification	Reported accuracies ranged from 85% (ensemble pretrained models) to 97.1% (multi-task deep learning combining segmentation and classification), with the best multimodal approach (MRI + PET) reaching 93.01% accuracy versus 89.55% for patch-based and 89.37% for slice-based single-modality methods
VECNN study (2024/2025), PMC11682981	Vision Transformer-equipped CNN (VECNN)	AD vs. MCI vs. healthy controls	3D MRI from the ADNI dataset (2,248 scans); hybrid transformer-CNN architecture for 3-way classification	Achieved 92.14% average accuracy, 93.27% sensitivity, 89.95% specificity, and 86.84% precision across the three diagnostic classes
Fine-tuned CNN study (2025), *Scientific Reports*, DOI 10.1038/s41598-	Transfer-learned, fine-tuned CNN	Alzheimer's disease classification	Model trained/tested on the Kaggle Alzheimer's MRI dataset and the OASIS	Achieved 99.4% accuracy on the Kaggle dataset and 98.2% on OASIS, demonstrating strong transfer-learning

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
025-86635-2			database	generalization across independent MRI datasets
Persson et al. (2018, reflected in later comparative studies), PubMed 29172642	NeuroQuant® automated hippocampal volumetry software	Alzheimer's disease dementia vs. non-dementia (subjective/mild cognitive impairment)	Compared automated hippocampal volumetry (NeuroQuant) against the visually-rated Scheltens medial temporal lobe atrophy (MTA) scale in 56 patients	Found strong correlation between automated hippocampal volume and visual MTA score; automated volumetry better discriminated AD dementia from non-dementia than the visual scale alone
Regional MRI volumetry study, PMC10839122	NeuroQuant automated regional brain volumetry	Cognitive impairment and dementia (86 patients)	Compared NeuroQuant regional volumes (hippocampus, temporal, frontal, parietal, occipital) against visual rating scales (MTA, GCA-f, PA) using ROC/AUC analysis	NeuroQuant hippocampal and temporal volumetry (AUC 0.74–0.80) outperformed visual MTA rating (AUC 0.69) for separating dementia from non-dementia; combining both methods only marginally increased diagnostic accuracy
NeuroQuant-assisted rating study (2025),	NeuroQuant volumetric report as a decision aid for	Subjective cognitive decline, MCI, and dementia	Two neuroradiologists rated MTA visually, with	Investigated whether AI-derived volumetric percentiles

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
PMC12480925	neuroradiologists	(n = 366, Oslo University Hospital)	and without access to age/sex-adjusted NeuroQuant hippocampal percentiles	improve the diagnostic accuracy of expert visual assessment, supporting a "human-plus-AI" hybrid model rather than pure automation
Frontotemporal dementia (FTD) subtyping study, PMC11713086	Automated brain volumetry combined with machine-learning classifiers	Frontotemporal dementia subtypes (behavioral variant, semantic variant, progressive non-fluent aphasia) vs. normal controls	Automated regional volumetry features used to train ML classifiers distinguishing FTD from controls and among FTD subtypes	Achieved 88–89% accuracy distinguishing FTD from normal controls, and 79–83% accuracy differentiating among the three FTD subtypes, supporting automated volumetry as a differential-diagnosis aid

3.3 Acute Ischemic Stroke (Perfusion, Occlusion, and Hemorrhage Detection)

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
CTP/LVO detection study (2024), PMC11572736	RAPID AI automated CT perfusion (CTP) software	Acute ischemic stroke with large vessel occlusion (LVO) and medium vessel occlusion (MeVO)	Screened 790 stroke patients (759 analyzed); RAPID-processed CTP maps (Tmax, CBV, CBF, MTT) compared against neuroradiologist-read CT angiography for detecting arterial occlusion	Automated CTP reliably ruled out large-vessel occlusion candidates for thrombectomy when interpreted consistently, though a subset of confirmed occlusions (arterial occlusion in 25 of 111 patients with "normal" CTP) were

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
				missed by perfusion alone, underscoring that automated CTP should complement, not replace, CTA
RAPID vs. Olea comparison (2019), PubMed 31562038	Head-to-head comparison of two FDA-approved automated CTP platforms (RAPID and Olea)	Acute ischemic stroke — infarct core estimation	141 AIS patients; CTP processed by both software packages and compared against follow-up diffusion-weighted MRI (DWI) as ground truth	For detecting large infarcts (≥70 mL), sensitivity/specificity were 73.7%/81.2% (RAPID) vs. 73.7%/68.3% (Olea); RAPID's core-infarct volume correlated more closely with DWI-confirmed infarct volume (rho = 0.64) than Olea (rho = 0.42), showing that different AI platforms are not interchangeable
RapidAI vs. Viz.ai comparison (2024), *American Journal of Neuroradiology*, PMC11286030	Head-to-head comparison of RapidAI and Viz.ai CTP output	Acute ischemic stroke — treatment-window eligibility decisions	129 AIS patients analyzed by both packages; correlation and concordance testing against DAWN/DEFUSE 3 thrombectomy-eligibility criteria	The two platforms were highly correlated for perfusion volumes, but concordance in patient-selection decisions varied by time window, highlighting the clinical importance of validating each specific AI package before adopting it
RAPID Non-Contrast CT (NCCT) Stroke platform study	Multi-module fully automated AI platform	Intracranial hemorrhage (ICH) and large vessel	Multicenter retrospective evaluation comparing AI	The AI platform outperformed general radiologists and was statistically non-

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
(2023), medRxiv preprint	(RAPID NCCT Stroke, iSchemaView)	occlusion detection on plain (non-contrast) CT	sensitivity/specificity for ICH and LVO detection to that of general radiologists and neuroradiologists	inferior to fellowship-trained neuroradiologists, supporting its use as a rapid triage/second-reader tool in acute stroke pathways
JLK PWI vs. RAPID validation study (2025), PMC12620487	JLK automated MRI perfusion-weighted imaging (PWI) software compared to RAPID	Acute ischemic stroke — MRI-based perfusion analysis (rather than CT-based)	Comparative validation of ischemic penumbra estimation and endovascular-therapy decision concordance between JLK PWI and RAPID	JLK PWI demonstrated high technical and clinical concordance with RAPID, supporting its use as a viable alternative automated platform for MRI-based (rather than CT-based) perfusion analysis

3.4 Brain Tumors (Segmentation and Volumetry)

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
Postoperative glioblastoma segmentation study (2023), PMC10558414	U-Net architecture trained via transfer learning (pretrained on BraTS2021)	Grade IV glioma (glioblastoma), pre- and post-operative tumor burden	237 MRI scans (71 preoperative, 166 postoperative) from 71 histologically-confirmed glioblastoma patients	The automatic segmentation algorithm produced reliable pre- and postoperative tumor delineation despite the additional challenge of postsurgical cavity artifacts and lower-quality real-world clinical imaging
Context deep-supervised U-Net study, PMC11752426	3D context deep-supervised U-Net	Brain tumor sub-region segmentation (whole tumor, tumor core, enhancing tumor)	Multiparametric MRI; automated segmentation volumes statistically compared to manual expert segmentation via	Average volumetric bias versus manual segmentation was only 1.25 cm^3 (whole tumor), 0.37 cm^3 (tumor core), and 0.28 cm^3 (enhancing tumor) — under 1.5% of

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
			Bland–Altman analysis and t-tests	respective tumor volumes — indicating the automated method closely reproduced manual measurements
Pediatric brain tumor multi-institutional study, *Neuro-Oncology Advances*, Oxford Academic	Deep learning-based automated segmentation and brain-tissue extraction	Pediatric brain tumors (multiple histologic subtypes)	Multi-institutional dataset; automated subregion volume ratios compared against manual segmentation	Strong agreement was found between automated and manual segmentation for enhancing-tumor and non-enhancing-tumor volume ratios (moderate agreement for edema ratio), supporting the model's potential to standardize tumor-subregion reporting across institutions
nnU-Net vs. DeepMedic pediatric tumor comparison, arXiv 2401.08404	Two competing deep-learning autosegmentation architectures (nnU-Net and DeepMedic)	Pediatric brain tumors — whole tumor and sub-region segmentation	Both models trained and tested on internal and external datasets; Dice score, sensitivity, and Hausdorff distance measured against manual ground-truth segmentation	nnU-Net significantly outperformed DeepMedic (Dice 0.90 vs. 0.82 for whole tumor, $p \leq 0.01$), demonstrating that choice of network architecture materially affects agreement with manual segmentation
AutoRANO validation (originally Chang et al., 2019, *Neuro-Oncology*;	Fully automated open-source deep-learning pipeline for glioma segmentation and	Glioblastoma treatment-response monitoring	Validated on 843 preoperative MRIs (4 institutions) and 713 longitudinal postoperative	Automated volumes showed excellent repeatability (intraclass correlation coefficient, ICC, 0.977–0.991) and strong agreement with

Authors (Year)	AI Method	Disease/Target	Methods	Results/Conclusion
validated through 2026), PMC13461318	RANO (Response Assessment in Neuro-Oncology) measurement		visits from 54 glioblastoma patients	manual expert measurements (ICC 0.915–0.965), supporting automated RANO 2.0 volumetric assessment as an improvement over manual/semi-automated response criteria
Automated pituitary adenoma volumetry study, PMC10805979	Ensemble of convolutional neural networks	Pituitary adenoma — pre- and postoperative tumor volume and extent-of-resection assessment	193 image sets used for training, 20 held out for external validation; automated volumetry compared with manual segmentation, which is noted to suffer from poor interrater agreement, especially postoperatively	Automated segmentation provided objective, reproducible tumor volumetry that addressed the interrater variability inherent to manual postoperative pituitary tumor measurement
Vestibular schwannoma segmentation study, PMC10169364	Deep neural network for automatic 3D segmentation	Vestibular schwannoma (a benign intracranial tumor requiring long-term MRI surveillance)	T1-weighted MRI; automatic 3D volumetric segmentation compared to conventional manual linear-dimension measurement	Automated segmentation was reported to improve detection/segmentation efficiency by about 30.8% in time savings compared to manual contouring, while also removing operator-dependent variability in measuring tumor growth over serial scans

4. Manual vs. AI-Automated Image Analysis: Direct Comparison Studies

A separate and growing body of literature has specifically compared manually performed image analysis against AI/automated analysis on the *same* patient images, rather than simply reporting AI performance in isolation. Key findings are summarized below by disease area.

4.1 Stroke — Infarct Volume Measurement

A 2025 comparison study (bioRxiv preprint) directly measured agreement between deep-learning-based automated infarct segmentation (JLK DWI software) and manual segmentation of diffusion-weighted imaging (DWI) in hyperacute stroke. Manual measurements were performed independently by two board-certified stroke neurologists and one neurology resident, with inter-rater and intra-rater agreement also assessed via repeat measurement roughly 13 months apart. The study reported excellent agreement between the automated deep-learning method and manual measurement, comparable to the agreement observed between different human raters — indicating that, for infarct volume quantification, AI-based measurement can match the reliability of experienced manual raters while removing the delay and rater-dependency of manual outlining.

4.2 Brain Tumors — Volumetric Comparison

Several of the tumor segmentation studies above were explicitly designed as manual-vs-automated comparisons:

- The **context deep-supervised U-Net study** (PMC11752426) found automated tumor sub-region volumes differed from manual expert segmentation by less than 1.5% on average, a difference within the range of normal inter-observer variability among human radiologists.
- The **AutoRANO validation** (PMC13461318) reported that automatically generated glioma volumes were not only in strong agreement with manual expert measurements (ICC up to 0.965) but were also *more repeatable* than manual and semi-automated methods — meaning that repeating the automated analysis on the same scan gave more consistent results than repeating manual measurement.
- The review of deep learning in brain tumor MRI (*npj Precision Oncology*, 2025) explicitly notes that manual 2D RANO (Response Assessment in Neuro-Oncology) measurements suffer from poor inter-rater reproducibility, and that automated deep-learning-based volumetric measurements have shown superior repeatability and reliability compared to human readers, while also being generated many orders of magnitude faster than manual annotation.
- The **vestibular schwannoma study** (PMC10169364) quantified a direct efficiency benefit, reporting roughly 30.8% time savings for automated segmentation over manual contouring, in addition to removing operator-dependent subjectivity.
- The **Wilms tumor study** (pediatric oncology, MRI-based; PMC10092966), while not strictly a neurology study, offers a relevant methodological finding: manual segmentation-based volumes were shown to differ systematically from simple radiological (linear-measurement-based) volumes, and automated deep-learning segmentation (median Dice 0.90) was proposed as a way to standardize what "manual" volumetry itself had failed to

standardize — illustrating that manual analysis is not a single fixed "gold standard" but is itself variable depending on technique.

4.3 Dementia — Hippocampal and Regional Volumetry vs. Visual Rating

The NeuroQuant literature (Section 3.2) constitutes one of the most direct and long-studied manual-vs-automated comparisons in neurology:

- Automated hippocampal volumetry consistently showed higher diagnostic accuracy (AUC 0.74–0.80) than the manually/visually-scored Scheltens MTA scale (AUC 0.69) for separating dementia from non-dementia (PMC10839122).
- A related quantitative-MTA (QMTA) study (PMC11017425) found that combining automated hippocampal and inferior lateral ventricle volumes into a composite index reached approximately 90% accuracy in differentiating Alzheimer's disease from controls, compared with 77% accuracy for the standard visual MTA scale alone.
- Rather than replacing manual/visual assessment outright, the most recent study in this line (PMC12480925, 2025, n = 366) tested whether giving neuroradiologists access to the automated NeuroQuant volumetric report improved the accuracy of their own visual rating — reflecting a shift in the literature toward "AI-assisted" rather than "AI-replacing" workflows.

4.4 Stroke Perfusion — Automated Software vs. Reference Standard

Because CT/MRI perfusion analysis is inherently too complex for real-time manual voxel-by-voxel calculation, the comparisons in this domain (Section 3.3) are largely software-vs-software or automated-software-vs-follow-up-imaging rather than automated-vs-purely-manual. Nonetheless, the RAPID NCCT Stroke platform study is notable for directly comparing AI performance against manual expert interpretation by general radiologists and neuroradiologists reading the same non-contrast CT scans for hemorrhage and large-vessel occlusion, finding the AI platform outperformed general radiologists and was non-inferior to neuroradiologists — a rare example of AI being compared not just to a "ground truth" but to practicing human readers under real diagnostic conditions.

5. Discussion

Across all four disease areas reviewed, a consistent pattern emerges:

Agreement with manual analysis is generally high for well-defined, single-structure or single-lesion-type tasks (hippocampal volume, tumor sub-region volume, infarct volume), with intraclass correlation coefficients frequently exceeding 0.90 and volumetric bias typically under 2%.

Reproducibility often favors the automated method. Manual/visual analysis — whether it is 2D RANO tumor measurement, MTA atrophy grading, or slice-by-slice lesion tracing — is repeatedly shown to have meaningful inter-rater and intra-rater variability that automated pipelines do not exhibit to the same degree.

Efficiency gains are substantial, with time savings on the order of 30% reported for tumor segmentation tasks, and near-instantaneous perfusion map generation for stroke triage that would be clinically impossible to perform manually within the required treatment windows.

Different AI platforms are not interchangeable. Head-to-head software comparisons (RAPID vs. Olea; RapidAI vs. Viz.ai; nnU-Net vs. DeepMedic) consistently found statistically meaningful differences between competing commercial or open-source AI tools, meaning validation results for one platform cannot simply be extrapolated to another.

The dominant clinical trend is AI-assisted rather than AI-replacing analysis. Several of the more recent studies (2023–2025) explicitly test whether giving a human expert access to AI-derived quantitative output improves that expert's own diagnostic accuracy, rather than testing whether AI can fully replace the expert — suggesting the field is converging on a hybrid human-AI post-processing model rather than full automation.

6. Conclusion

Over the past decade, AI-based post-processing tools — most built on convolutional neural network and U-Net architectures — have moved from experimental proof-of-concept studies to validated, in some cases FDA-cleared, components of routine neurological image analysis in multiple sclerosis, Alzheimer's disease and dementia, acute ischemic stroke, and brain tumor management. Direct comparison studies show that automated analysis generally matches manual expert analysis in accuracy while exceeding it in reproducibility and speed, though meaningful differences exist between competing AI platforms, and the current clinical trajectory favors combining AI quantification with expert interpretation rather than removing the expert from the workflow entirely.

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