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ARTIFICIAL INTELLIGENCE–BASED DETERMINATION OF CEREBRAL HEMISPHERE MORPHOMETRIC PARAMETERS USING MAGNETIC RESONANCE IMAGING (MRI)

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Abstract
Quantitative morphometric analysis of cerebral hemispheres using magnetic resonance imaging (MRI) has become an essential component of modern neuroradiology. Structural parameters such as hemisphere volume, cortical thickness, and surface area serve as sensitive biomarkers for neurodegenerative, neurovascular, and neurodevelopmental disorders. However, traditional manual and semi-automated segmentation approaches are time-consuming and prone to inter-observer variability. Recent advances in artificial intelligence (AI), especially deep learning-based segmentation models, have demonstrated high accuracy in structural brain analysis. This study

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provides a comprehensive AI-based framework for automated cerebral hemisphere morphometry and describes its implementation via the NeuroMorph AI web platform. The proposed system combines deep learning segmentation, volumetric computing, cortical surface reconstruction, and structural digital reporting by analyzing MRI images, providing a scalable and clinically applicable solution that is compatible with the modern healthcare digital transformation.

Keywords: Artificial Intelligence; Magnetic Resonance Imaging (MRI); Cerebral Hemisphere Morphometry; Deep Learning Segmentation; Cortical Thickness Analysis; Brain Volumetry; Digital Health Integration.

Introduction

Magnetic resonance imaging remains the reference standard for structural brain evaluation due to its superior soft-tissue contrast resolution and non-ionizing imaging properties. Over the past two decades, quantitative morphometric analysis has evolved from purely research-based methodologies into clinically relevant tools for diagnosis and disease monitoring. Volumetric reductions in cerebral hemispheres, focal cortical thinning, and asymmetry indices are increasingly recognized as early indicators of neurodegenerative conditions such as Alzheimer's disease and Parkinson's disease, as well as markers of cerebrovascular injury and traumatic brain damage [6,8].

Despite the clinical importance of morphometric biomarkers, their widespread use is limited by technical and operational constraints. Traditional morphometry relies mainly on manual or atlas-based segmentation, which requires significant expertise and computational time. NueroMorph AI solves these problems and simplifies the doctor's work by providing a systematic approach and statistical presentation of the results.

In recent years, scientific research on solving the above-mentioned problems has led to a deep study of this area. Convolutional neural networks, especially encoder-decoder architectures such as U-Net variants, have demonstrated strong performance in brain MRI segmentation tasks. As reported in the book "Radiography", automated deep learning systems consistently outperform classical segmentation methods in terms of speed and structural delineation accuracy. Other scientists have also noted that modern deep neural networks allow for reliable separation of cortical and subcortical structures even in heterogeneous imaging datasets [7,9].

Clinical studies also confirm the potential of AI-based analysis systems and their ability to provide priority solutions. Several researchers have demonstrated strong agreement between AI-derived brain volume measurements and manual expert assessments in clinical trials of patients presenting with memory complaints, and have shown that AI-based volume quantification maintains consistency across ultra-low-field and conventional 3T MRI systems and overcomes problems related to scanner variability and alignment [1,2].

Together, these advances demonstrate that AI-based morphometry has reached a level suitable for clinical integration. However, moving from algorithm development to practical clinical deployment requires a scalable digital infrastructure and user-friendly implementation. The NeuroMorph AI platform is designed to bridge this translational gap.

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This platform analyzes MRI tomograms and provides statistical information on brain structural symmetry, cortical morphology integrity index, groove depth assessment, cortical thickness, gray matter volume, white matter integrity, gyral complexity index, and hemispheric asymmetry.

The program is loaded with a database of normal and pathological states, and the AI compares the results to normal. The database is implemented using the OpenNeuro open database, and the AI is specifically programmed for the image comparison function.

Materials and Methods

High-resolution T1-weighted MRI datasets acquired on 3T scanners formed the basis of this study. Imaging protocols were standardized to ensure isotropic voxel resolution and optimal gray–white matter contrast. Preprocessing included bias field correction to eliminate intensity inhomogeneity, skull stripping to remove extracranial tissues, intensity normalization for intersubject comparability, and spatial registration to a standardized anatomical template [4,5].

Study Design and Data Sources

This study employed a retrospective computational modeling design for the development and validation of the NeuroMorph AI platform. Structural brain MRI datasets were obtained from open-access repositories, primarily the OpenNeuro database, which provides standardized neuroimaging datasets acquired under ethically approved research protocols. Both neurologically healthy subjects and patients with structural brain pathology were included to ensure robust model training and comparative analysis.

Normal reference datasets were curated to establish baseline morphometric distributions across age and sex categories. Pathological datasets included cases with neurodegenerative, neurovascular, and structural abnormalities to improve model generalizability. All imaging data were anonymized prior to analysis.

MRI Acquisition Parameters

Only high-resolution T1-weighted MRI scans with isotropic voxel resolution (≤ 1 mm^3) were included. Scans were acquired using 3T MRI systems to ensure adequate gray–white matter contrast. DICOM images were converted into NIfTI format for standardized preprocessing.

Image Preprocessing Pipeline

All MRI datasets underwent a standardized preprocessing workflow prior to AI inference. The preprocessing steps included: Intensity non-uniformity correction using N4 bias field correction to eliminate signal inhomogeneity. Skull stripping to remove non-brain tissues and extracranial structures. Spatial normalization and affine registration to a standard anatomical template (MNI space) to ensure intersubject comparability. Intensity normalization to harmonize signal distribution across different scanners and acquisition protocols. Noise reduction through Gaussian smoothing where necessary. This standardized preprocessing minimized scanner-dependent variability and improved segmentation robustness.

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AI Model Architecture

NeuroMorph AI utilizes a deep convolutional neural network based on a modified 3D U-Net architecture optimized for volumetric MRI segmentation. The encoder–decoder framework allows multiscale feature extraction while preserving fine anatomical boundaries.

The model was trained using supervised learning on annotated MRI datasets with expert-validated segmentation masks. Data augmentation techniques, including rotation, flipping, intensity scaling, and elastic deformation, were applied to increase model generalizability [3].

For image comparison and structural similarity analysis, a secondary deep metric learning module was implemented. This component uses feature embedding vectors extracted from intermediate convolutional layers to compare uploaded MRI scans with the normative database. Cosine similarity and Euclidean distance metrics were applied to quantify deviation from normal structural patterns.

Morphometric Parameter Extraction

Following automated segmentation, the platform computes multiple morphometric indices: Cerebral structural symmetry score was calculated by quantifying volumetric and surface differences between left and right hemispheres.

Cortical morphology integrity index was derived from surface smoothness metrics and cortical continuity measures. Sulcal depth assessment was performed using curvature-based surface modeling algorithms that measure depth relative to a convex hull representation of the cortex. Cortical thickness was computed as the distance between white matter and pial surfaces using Laplacian-based surface reconstruction methods.

Gray matter volume was calculated by voxel summation within segmented gray matter masks. White matter integrity index was derived from volumetric continuity and segmentation confidence maps.

Gyrification complexity index was computed based on local curvature and folding patterns of the cortical surface.

Hemispheric asymmetry indices were calculated using normalized difference formulas: $AI = (Left - Right) / ((Left + Right)/2)$

All parameters were expressed in standardized units and normalized against age-adjusted reference distributions.

Normal–Pathological Comparative Framework

The NeuroMorph AI system incorporates a reference normative database derived from OpenNeuro healthy control datasets. Statistical distributions for each morphometric parameter were computed, including mean, standard deviation, percentile ranges, and z-score normalization.

When a new MRI scan is uploaded, the system compares extracted morphometric features against normative distributions using z-score transformation. Deviations beyond ±2 standard deviations are flagged as statistically significant structural abnormalities.

Additionally, a supervised classification layer trained on pathological cases predicts probability scores for structural abnormality presence. The output includes both quantitative deviation indices and probabilistic risk assessment.

Statistical Analysis

Statistical analysis was performed using Python-based scientific libraries. Pearson correlation coefficients were calculated to assess agreement between AI-derived measurements and reference standards. Dice similarity coefficient was used to evaluate segmentation accuracy.

Independent t-tests and ANOVA were applied to compare morphometric parameters between normal and pathological groups. Statistical significance was defined as $p < 0.05$.

Receiver operating characteristic (ROC) curve analysis was conducted to evaluate the classification performance of the AI system in distinguishing normal from pathological cases.

System Deployment and Clinical Interface

The NeuroMorph AI platform was implemented as a secure web-based application. Backend AI inference was deployed on GPU-accelerated servers to ensure efficient processing. The frontend interface allows DICOM upload, segmentation visualization overlays, statistical summary display, and structured PDF report generation.

All processed data are encrypted and stored in compliance with medical data protection standards.

Results

A total of 412 structural T1-weighted MRI scans were included in the final analysis, comprising 268 neurologically healthy subjects and 144 patients with confirmed structural brain pathology. The NeuroMorph AI platform successfully processed all scans without computational failure, with an average processing time of 94 ± 12 seconds per scan.

Segmentation Performance

The automated segmentation module demonstrated high spatial accuracy. The mean Dice similarity coefficient reached 0.94 for gray matter segmentation and 0.92 for white matter segmentation when compared to expert-annotated reference masks. Cortical surface reconstruction showed strong anatomical concordance, with a mean surface distance error of 0.38 mm.

Inter-method agreement analysis between AI-derived volumetric measures and reference standard software demonstrated a Pearson correlation coefficient of $r = 0.97$ ($p < 0.001$), indicating strong reliability of volumetric extraction.

Morphometric Quantification

Neuro Morph AI successfully extracted all predefined morphometric indices, including cortical thickness, gray matter volume, white matter integrity index, sulcal depth, gyrification complexity index, hemispheric symmetry score, and asymmetry indices.

In the healthy cohort, mean global cortical thickness was 2.61 ± 0.14 mm, while pathological cases demonstrated a statistically significant reduction (2.34 ± 0.19 mm, $p < 0.001$). Gray matter volume showed a mean decrease of 11.8% in pathological cases compared to normative controls.

The hemispheric asymmetry index remained within ±3% in healthy individuals but exceeded 8% in 63% of pathological cases. Gyrification complexity index was significantly reduced in neurodegenerative cases ($p = 0.002$), while sulcal depth variability increased in patients with cortical atrophy.

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White matter integrity index demonstrated statistically significant reduction in pathological cases ($p < 0.001$), consistent with structural disruption patterns.

Normal–Pathological Comparison Framework

Z-score–based deviation analysis revealed that 71% of pathological scans demonstrated at least three morphometric parameters exceeding ±2 standard deviations from normative reference distributions. In contrast, only 6% of healthy controls showed isolated borderline deviations.

Receiver operating characteristic (ROC) analysis demonstrated strong discriminative capacity of the combined morphometric model. The area under the curve (AUC) reached 0.93 for distinguishing normal from pathological cases. Sensitivity was 0.89, and specificity was 0.91 at the optimal threshold.

Structural Symmetry and Asymmetry Analysis

The structural symmetry score was significantly lower in pathological cohorts (0.87 ± 0.06) compared to controls (0.96 ± 0.03, $p < 0.001$). Hemispheric volumetric asymmetry was particularly pronounced in cases with focal lesions and cortical degeneration.

Quantitative asymmetry modeling demonstrated that AI-based comparison against the normative OpenNeuro reference database improved abnormality detection accuracy by 14% compared to volumetry-only assessment.

Clinical Interpretability

Statistical report outputs generated by NeuroMorph AI allowed structured visualization of morphometric deviation profiles. Multivariate analysis confirmed that combined cortical thickness, gray matter volume, and gyrification complexity indices significantly contributed to predictive classification models ($p < 0.001$).

Overall classification accuracy of the system reached 90.8%, demonstrating strong diagnostic support potential.

Discussion

The integration of AI-driven segmentation into MRI morphometry represents a paradigm shift in neuroradiology. Automated systems provide objective, reproducible, and scalable analysis of cerebral structures, minimizing operator dependency. As highlighted in recent comprehensive reviews, deep learning models have reached performance levels comparable to expert manual segmentation in many neuroimaging tasks.

One of the major advantages of AI-based morphometry lies in its potential for early disease detection. Subtle cortical thinning or hemispheric volume reduction may precede overt clinical symptoms. Automated systems allow systematic screening and longitudinal tracking of such changes, which is particularly relevant in aging populations and high-risk cohorts.

Another critical aspect is interoperability within digital healthcare ecosystems. Modern radiology departments increasingly rely on integrated digital solutions, including PACS systems, electronic health records, and telemedicine infrastructures. AI-powered morphometric platforms such as Neuro

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Morph AI align with broader healthcare digitalization trends by enabling standardized data exchange, remote analysis capabilities, and structured quantitative reporting.

Conclusion

The present study demonstrates that the NeuroMorph AI platform enables reliable, automated, and statistically robust morphometric analysis of cerebral hemispheres using structural MRI data. By integrating deep learning–based segmentation, surface reconstruction algorithms, and normative database comparison, the system provides comprehensive quantitative evaluation of cortical and subcortical structures.

The platform successfully quantified cortical thickness, gray matter volume, white matter integrity index, sulcal depth, gyrification complexity, hemispheric symmetry, and asymmetry indices with high spatial accuracy and strong agreement with reference standards. The integration of a normative database derived from OpenNeuro significantly enhanced abnormality detection through z-score–based deviation modeling, allowing objective differentiation between normal and pathological structural patterns.

Importantly, the combined morphometric framework demonstrated high diagnostic discrimination capacity, with strong sensitivity and specificity in identifying structural abnormalities. The ability to simultaneously assess multiple morphometric parameters provides a multidimensional structural profile rather than isolated volumetric measurements, thereby improving clinical interpretability.

NeuroMorph AI represents a scalable and deployable digital solution for radiology and neuroimaging workflows. Its web-based architecture enables standardized MRI analysis, reduces operator dependency, and supports decision-making through statistically structured outputs. The automated comparison mechanism between patient-specific MRI data and normative structural distributions offers potential for early detection of subtle morphological alterations that may not be visually apparent in conventional radiological assessment.

Future research should focus on multicenter validation, integration of multimodal MRI sequences, longitudinal progression modeling, and clinical outcome correlation to further strengthen translational applicability.

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