International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 2313-2321
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Integrating Deep Learning and MRQy: A Comprehensive Framework for Early Detection and Quality Control of Brain Tumors in MRI Images using Python

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Article Info:

DOI: 10.22399/ijcesen.1471
Received : 01 February 2025
Accepted : 08 April 2025

Keywords :

Brain Tumor Detection,
Deep Learning,
MRI Quality Control,
MRQy.

Abstract:

The early detection of brain tumors is crucial for timely medical intervention and improved patient survival rates. Magnetic Resonance Imaging (MRI) is the gold standard for brain tumor diagnosis due to its superior soft-tissue contrast and non-invasive nature. However, variations in MRI quality, including noise, artifacts, and scanner inconsistencies, can impact diagnostic accuracy. This study aims to de-velop a Python-based deep-learning model for the early detection of brain tumors in MRI scans while integrating an automated quality control system using MRQy. MRQy, an open-source tool, facilitates quality assessment by evaluating signal-to-noise ratios (SNR), contrast-to-noise ratios (CNR), and motion-related artifacts. The deep learning model will be trained on a meticulously curated dataset, ensur-ing high-quality and artifact-free MRI images. By combining MRQy's quality control capabilities with deep learning techniques, the model is expected to en-hance tumor detection accuracy and reduce false-positive and false-negative rates. Furthermore, this research underscores the significance of standardized imaging protocols to minimize variability across scanners and institutions, ensuring repro-ducibility in clinical AI applications. The proposed approach leverages modern convolutional neural networks (CNNs) and transfer learning techniques, incorpo-rating pre-trained architectures such as Res Net and Efficient Net to enhance fea-ture extraction. By integrating MRQy-based quality assessment with AI-driven tumor classification, this study aims to optimize MRI-based diagnostics, reduce human error, and improve clinical outcomes. The findings contribute to the ad-vancement of AI-powered medical imaging and highlight the importance of MRI quality control in deep-learning applications.

1. Introduction

To mitigate variability in MRI quality, establishing standardized imaging protocols across different manufacturers is essential to ensure scan consistency. Implementing uniform acquisition settings can help minimize discrepancies in key quality metrics such as signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), and motion artifacts. Standardization efforts should focus on harmonizing scanner calibration, voxel resolution, and acquisition parameters to create reproducible and high-quality imaging datasets. Motion artifacts, as reflected in metrics such as the Entropy Focus Criterion (EFC) and Foreground-Background Energy Ratio (FBER), significantly degrade MRI quality and compromise the accuracy of computational imaging models. Incorporating real-time motion correction techniques into MRI acquisition workflows can substantially improve image fidelity [1-3]. Advanced motion tracking software and patient monitoring mechanisms should be integrated to detect and compensate for movement during scans, reducing errors in clinical imaging and ensuring high-quality data for AI-based analysis. To enhance the efficiency of MRI quality assessments, the MRQy framework should be seamlessly incorporated into routine imaging pipelines.

Automating quality screening prior to analysis can streamline the curation of high-quality MRI datasets. Future iterations of MRQy could introduce real-time feedback mechanisms that alert operators to potential quality issues during scans, enabling immediate corrective actions and reducing the likelihood of acquiring suboptimal data.

Expanding the dataset and employing deep learning models, such as Convolutional Neural Networks (CNNs) and Vision Transformers, can further refine MRI scan classification accuracy. Leveraging transfer learning from larger medical imaging datasets could enhance model generalizability, enabling improved quality assessment across diverse MRI protocols and clinical settings. Training AI models on high-quality scans validated through MRQy will ensure robust predictions and minimize errors in tumor detection and segmentation. A deeper investigation into the relationship between Image Quality Metrics (IQMs) and diagnostic accuracy is essential to understanding the clinical impact of MRI quality. Future studies should assess how low-quality scans influence radiological interpretations and AI-based tumor classification. Evaluating the role of quality control in reducing false positives and false negatives in deep learning models will provide valuable insights into the importance of maintaining high imaging standards in medical research and clinical applications [4,5].

This study underscores the critical role of MRI quality assessment in ensuring reliable imaging for both clinical and research applications. The findings highlight the effectiveness of MRQy as an automated quality control tool, the potential of deep learning in MRI scan classification, and the necessity for standardization in imaging protocols. By integrating AI-driven quality assessments with automated QC frameworks, future MRI workflows can achieve superior image consistency, enhanced diagnostic accuracy, and optimized clinical decision-making processes.

2. MRQy: An Open-Source Solution for Automated Quality Control in MRI Data Analysis

The availability of publicly accessible imaging repositories, such as The Cancer Imaging Archive (TCIA), has significantly facilitated advancements in machine learning and deep learning applications for radiographic imaging in oncological research. With more than 2,500 MRI scans covering 26 anatomical sites collected from multiple institutions and diverse imaging equipment, ensuring consistency and reliability in these datasets is crucial for developing accurate computational imaging models. A significant challenge in utilizing these datasets for artificial intelligence (AI) model training lies in curating MRI scans with minimal artifacts to ensure dataset homogeneity. This standardization enhances model reproducibility and generalizability across unseen data. An essential aspect of this process is the quantitative assessment of variations and artifacts in MRI datasets, which serves as a key determinant in evaluating the transferability of deep learning models [1,2].

The following factors play a critical role in MRI dataset variability and its impact on computational imaging:

1. **Site- and Scanner-Specific Variations**
   a. Differences in acquisition parameters, such as echo time (TE), repetition time (TR), and voxel resolution, can introduce batch effects, leading to inconsistencies across different imaging sites.
   b. For instance, The Cancer Genome Atlas Glioblastoma Multiforme (TCGA-GBM) dataset exemplifies variations in image dimensions and voxel sizes across multiple acquisition centers.
2. **Imaging Artifacts Impacting Model Performance**
   a. Magnetic field inhomogeneity, aliasing, motion blur, ringing artifacts, and noise significantly degrade MRI quality, causing variations that can impair the performance of computational models.
   b. Addressing and correcting such artifacts before integrating MRI scans into deep learning pipelines is necessary to prevent bias and inconsistencies in AI-based predictions.

Ensuring consistency and quality in MRI datasets is crucial for validating radiomics and deep learning models. A major limitation of manual MRI quality assessments is their lack of scalability, as well as inter-rater variability, which makes subjective quality ratings unreliable. Given the increasing volume of imaging data in repositories like TCIA, relying solely on human inspection for MRI quality assessment is neither practical nor effective in identifying subtle variations. These challenges underscore the urgent need for automated quality control (QC) tools that efficiently curate MRI datasets, ensuring they are free from artifacts and standardized for computational analysis.

2.1 Automated MRI Quality Control Approaches

Efforts to develop automated MRI QC solutions have led to the emergence of Image Quality Metrics (IQMs) and standardized Quality Assessment Protocols (QAPs). These protocols include:

Signal-to-Noise Ratio (SNR)

SNR is a fundamental metric used to quantify the clarity of an MRI image by measuring the ratio of the mean signal intensity in a region of interest to the standard deviation of the background noise. A higher SNR indicates a clearer image with minimal noise, whereas a lower SNR suggests degraded image quality due to excessive noise. It is given as eq (1) [6-8].

$$SNR = \frac{\mu_F}{\sigma_B} \qquad (1)$$

Where:

μ_F = Mean intensity of the foreground (e.g., tumor region in MRI)

σ_B = Standard deviation of background intensity (noise levels)

- High SNR (>20 dB): High-quality image with low noise, ensuring accurate interpretation.
- Moderate SNR (10–20 dB): Acceptable image quality with some noise but still usable for analysis.
- Low SNR (<10 dB): Poor-quality image, with significant noise, affecting clinical reliability.
- Factors Affecting SNR:
  - Scanner Strength: Higher Tesla (T) MRI scanners (e.g., 3T vs. 1.5T) improve SNR.
  - Voxel Size: Smaller voxels reduce noise but may lower SNR.
  - Patient Motion: Movement increases noise, reducing SNR.
- Importance in Deep Learning: High SNR ensures deep learning models learn from clear, high-quality images, reducing mis classification risks in brain tumor detection [7,8] .

Contrast-to-Noise Ratio (CNR)

CNR measures the ability to differentiate tumors or abnormalities from surrounding healthy tissue by evaluating the difference in signal intensity relative to noise. A higher CNR improves visibility of the structure of interest. Deep learning models rely on high CNR images for accurate tumor classification. MRQy helps detect low-CNR scans, ensuring that only high-contrast images are used for training. It is given as eq (2).

$$CNR = \frac{\mu_F - \mu_B}{\sigma_B} \qquad (2)$$

Where:

μ_F = Mean intensity of the tumor region

μ_B= Mean intensity of the background region

σ_B= Background noise standard deviation

- High CNR (>10): Tumor is well-differentiated from background, aiding AI-based seg]
- Moderate CNR (5–10): Tumor is partially visible but may require contrast enhancement.
- Low CNR (<5): Poor contrast, making tumor detection difficult.
- Factors Affecting CNR: Magnetic Field Strength: Higher field MRI (e.g., 3T) improves.
- Contrast Agents: Gadolinium-enhanced MRI improves tumor visibility.
- Tissue Properties: Edema and necrosis affect CNR values.

Coefficient of Joint Variation (CJV)

CJV assesses intensity uniformity across an MRI scan, helping detect variations caused by scanner artifacts, field inhomogeneity, or bias in signal distribution. It is given as eq (3).

$$CJV = \frac{\sigma_F + \sigma_B}{|\mu_F - \mu_B|} \qquad (3)$$

Where:

σ_F = Standard deviation of the foreground intensity (tumor or anatomical structure)

σ_B = Standard deviation of the background intensity (non-tissue regions)

μ_F = Mean intensity of the foreground

μ_B= Mean intensity of the background

- High CJV (> threshold): Significant intensity variations, making segmentation difficult.
- Moderate CJV: Some variations, requiring normalization.
- Low CJV: Consistent intensity distribution and ideal for based analysis.
- Factors Affecting CJV: Field inhomogeneity uneven field strength across the scan affects intensity.
- Scanner variability: Different MRI manufacturers may introduce intensity differences.
- Multi-Site Studies: Variability in imaging protocols can impact CJV.
- Importance in AI-Based Imaging: Deep learning models require uniform intensity distribution for accurate feature extraction.
- MRQy identifies scans with high CJV flagging them for correction before AI training.

Entropy Focus Criterion (EFC)

EFC measures the degree of randomness in intensity variations in an MRI scan. High entropy suggests motion artifacts, blurring, or image distortion that can affect segmentation and diagnosis. It is given as eq (4).

$$EFC = \frac{NM}{\sqrt{NM}} log\left(\frac{E}{\sqrt{NM}}\right) \qquad (4)$$

Where:

N and M are image dimensions (number of pixels)

E is the Shannon entropy of intensity distributions.

- High EFC (> threshold): Indicates motion artifacts, requiring correction.
- Moderate EFC: Some distortions, but acceptable for analysis.
- Low EFC: Minimal artifacts, ensuring optimal clarity.
- Factors Affecting EFC: Patient Motion: Motion during scanning increases entropy values. Long Scan Durations: Extended acquisition time leads to motion artifacts. Scanner Hardware: Coil sensitivity and field strength impact EFC.
- Impact on AI Models: Motion artifacts severely impact tumor segmentation accuracy. MRQy integrates EFC-based quality control to detect and filter motion-affected scans before AI analysis.

2.2 Supervised MRI Quality Control Tools

One of the widely adopted QC tools, MRIQC, is a supervised method that classifies MRI scans based on expert-defined quality annotations. MRIQC utilizes web-based interfaces, enabling expert reviewers to seamlessly interact with the system and conduct large-scale MRI quality assessments, several MRI QC tools have been designed for brain imaging, such as [8-11]:

a. Qoala-T (FreeSurfer-Specific MRI Quality Control Tool): is a machine-learning-based tool designed for automated quality control of FreeSurfer-processed MRI data. It automates the validation of structural MRI scans, reducing reliance on manual inspections and improving efficiency in large-scale neuroimaging studies.
b. LABQA2GO: A Generalized MRI Quality Assessment Tool: is a fully automated tool capable of performing unsupervised MRI quality assessments across various imaging modalities. Unlike Qoala-T, which is specific to FreeSurfer-processed MRI scans, LABQA2GO evaluates raw MRI images and generates detailed quality reports, making it suitable for multi-site imaging studies.

However, most existing MRI QC tools are limited to brain imaging and may lack generalizability for analyzing MRI datasets from different anatomical sites. This highlights the need for a scalable, unsupervised quality control framework that can ensure MRI dataset integrity across a wide range of imaging applications.

2.3 MRQy: An Open-Source Framework for MRI Quality Control

MRQy was developed as an open-source quality control tool tailored for analyzing large-scale MRI datasets. Built upon the histo QC python framework, MRQy integrates multiple quality assessment modules to handle diverse MRI datasets efficiently. Key Features of MRQy [9-11]:

a. Automatic Foreground Detection

MRQy automatically detects the foreground region in an MRI scan, regardless of the anatomical site. This step is crucial for isolating the region of interest (ROI) and ensuring accurate quality assessments.

b. Extraction of Imaging-Specific Metadata and Quality Metrics

MRQy extracts a wide range of imaging-specific metadata and quality measures applicable to any MRI sequence. These extracted metrics provide valuable insights into image quality, helping detect inconsistencies and batch effects.

c. Computation of Quality Trends

MRQy computes statistical representations that capture MRI quality trends within a dataset. These trends enable the identification of scanner-related artifacts and site-specific imaging variations.

d. Interactive HTML5-Based Visualization

MRQy features an interactive front-end interface that allows users to analyze computed MRI quality trends intuitively. The web-based dashboard enables researchers to quickly identify batch effects, artifacts, and low-quality scans.

3. Genomic Data Commons (GDC): A Centralized Cancer Genomics Platform

The Genomic Data Commons (GDC), established by the National Cancer Institute (NCI), is a centralized platform for harmonized genomic and clinical cancer data. It integrates molecular data from major cancer research projects, facilitating precision medicine, biomarker discovery, and AI-driven research [12-17]. Figure 1 illustrates a web platform that facilitates interactive data exploration, visualization, and downloading of datasets. Figure 2 illustrates an enhanced command-line tool for downloading large datasets quickly and efficiently.

3.1 Key Features

a. Centralized Data Repository

Provides access to multi-omic datasets, including whole-genome sequencing (WGS), RNA-Seq, DNA methylation, and clinical metadata. Consolidates data from TCGA, TARGET, and CGCI, covering various cancer types.

b. Data Standardization

Ensure consistency across studies by harmonizing sequencing data to standard reference genomes. Applies quality control measures for reliable.

Figure 1. *A web-based platform that facilitates interactive data exploration, visualization and dataset downloads*

research outcomes

c. Data Accessibility

Open-access data: Includes a summary of clinical information and metadata. Controlled-access data: Raw sequencing files requiring authorization via dB Gap.

3.2 Tools & Access Methods

GDC Data Portal

A web-based interface for exploring and downloading datasets. GDC API – Enables automated data retrieval using Python, R, and other programming languages.

GDC Data Transfer Tool (DTT)

The GDC accelerates discoveries in oncology, leading to better diagnostics and improved patient care. From by a command-line utility for large-scale data downloads in applications for cancer research supports tumor biology studies, machine learning models, personalized treatment strategies, enhances genomic guided clinical trials and driven cancer diagnostics. By providing standardized, high-quality genomic data.

4. Results

4.1 Evaluation of MRI Quality Control Using MRQy

This section evaluates the deep learning driven by the MRI quality control framework, assessing its accuracy and effectiveness in identifying quality discrepancies across MRI scans. We analyze MRQy's performance as an automated quality control tool, where show figure 3 interface, the results obtained, compare it with existing methods and high lighting its strengths and limitations. The analysis, performed using MRQy, took 54.22 minutes to process all 21 datasets within the TCGA-GBM collection. As shown in figure 4.

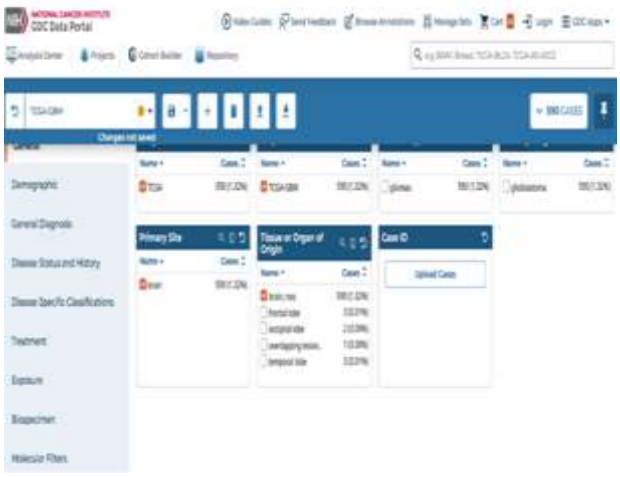


Figure 2. *A command-line utility optimized for fast and efficient downloading of large datasets.*

Since these MRI scans were acquired under diverse environmental conditions, employing different scanner equipment and imaging protocols, this cohort captures typical data variations and imaging artifacts. All 21 studies were obtained as DICOM files from TCIA. Analysis, datasets within the TCGA-GBM collection. The table 1 presents the results obtained.

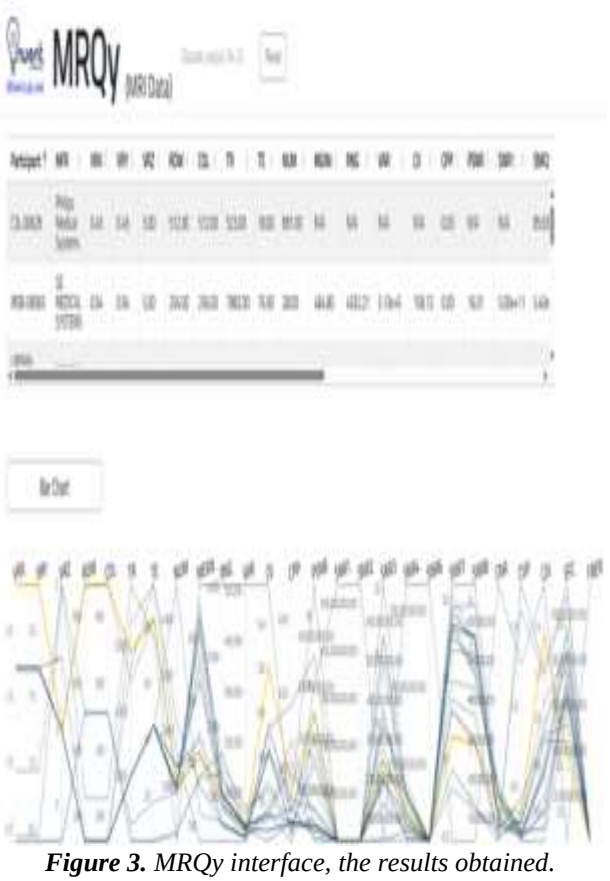


Figure 3. *MRQy interface, the results obtained.*

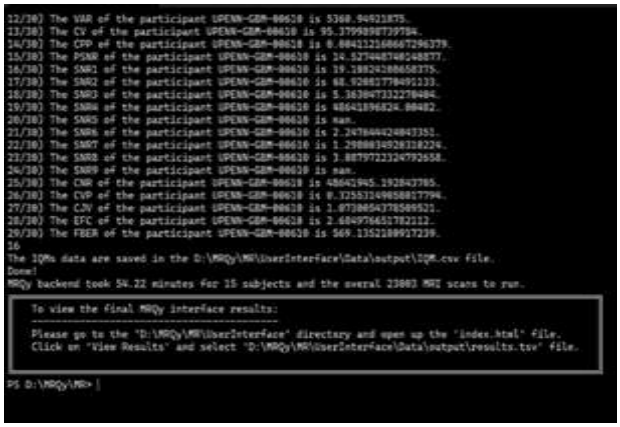


Figure 4. *the processing time for analyzing the TCGA-GBM dataset.*

As explain an MRI Quality Clustering (Based on SNR and CNR) in figure 5

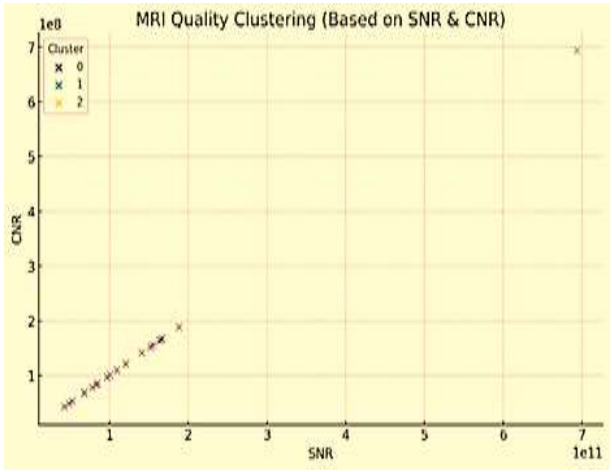
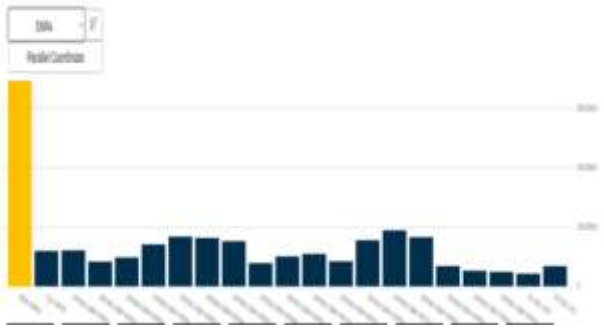
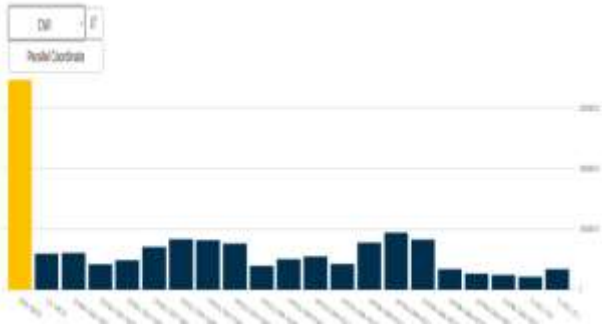


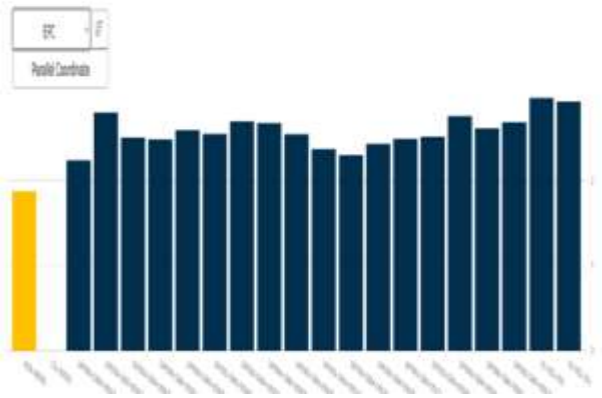
Figure 5.*MRI Quality Clustering (Based on SNR & CNR)*



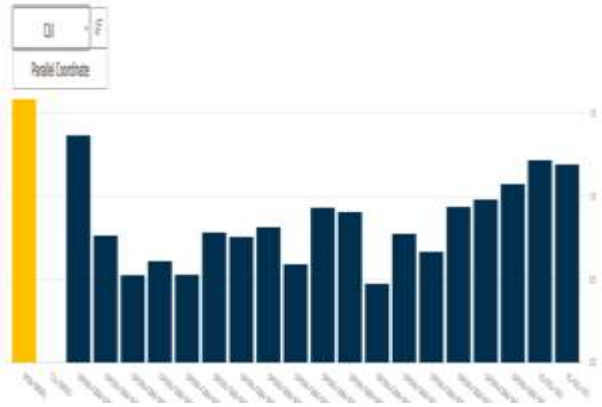
(a)



(b)

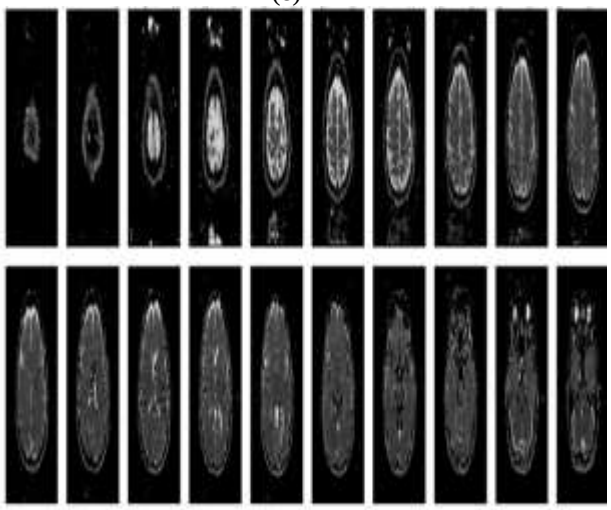


(c)



(d)

(e)



(f)

Figure 6. *Evaluation of critical MRI quality control (MRQy) metrics across multiple participants (MSB-08583) with the highest values.*

To ensure a comprehensive assessment, MRI scans from 21 participants across SIEMENS, GE, and PHILIPS scanners were analyzed. This dataset allowed us to examine variability in image quality, manufacturer differences, and scan consistency. The findings contribute to advancing automated MRI quality control, promoting standardized, high-fidelity imaging across different MRI systems. Where in figure 6 shown an MRI quality clustering results (a-b-c-d-e-f) Evaluation of critical MRI quality control (MRQy) metrics across multiple participants (MSB-08583) with the highest values.

Table 1. *Summary of the Integrated Quality Index for each participant.*

N	Participant	SNR4	CNR	EFC	CJV	FBER
1	MSB-08583	6.94E+11	6.94E+08	1.874216	1.583317	1.13E+11
2	C3L-00629	1.19E+11	1.19E+08	0	0	0
3	UPENN-GBM-00001	1.21E+11	1.21E+08	2.23794	1.365744	6592801
4	UPENN-GBM-00002	8.35E+10	83549070	2.799209	0.763593	343.356
5	UPENN-GBM-00003	9.69E+10	96899473	2.504477	0.525004	40079138
6	UPENN-GBM-00004	1.41E+11	1.41E+08	2.484091	0.609003	30324447
7	UPENN-GBM-00005	1.67E+11	1.67E+08	2.592387	0.527694	59844876
8	UPENN-GBM-00006	1.63E+11	1.63E+08	2.547964	0.781421	72568963
9	UPENN-GBM-00007	1.52E+11	1.52E+08	2.69615	0.755186	424.4813
10	UPENN-GBM-00008	7.83E+10	78319966	2.675156	0.813325	357.8978
11	UPENN-GBM-00009	1.01E+11	1.01E+08	2.543837	0.591134	72337260
12	UPENN-GBM-00010	1.09E+11	1.09E+08	2.370176	0.931048	97659533
13	UPENN-GBM-00025	8.47E+10	84696321	2.299507	0.904773	1914.493
14	UPENN-GBM-00056	1.56E+11	1.56E+08	2.429729	0.47299	21025441
15	UPENN-GBM-00314	1.88E+11	1.88E+08	2.490497	0.773585	18234540
16	UPENN-GBM-00590	1.65E+11	1.65E+08	2.514053	0.665947	2497577
17	UPENN-GBM-00595	6.81E+10	68096657	2.757371	0.936176	623.7988
18	UPENN-GBM-00604	5.27E+10	52658602	2.613627	0.980108	151.6822
19	UPENN-GBM-00610	4.86E+10	48641945	2.684977	1.073005	569.1352
20	VS-SEG-200	4.26E+10	42580885	2.970894	1.215766	94.73365
21	VS-SEG-201	6.79E+10	67917301	2.9277	1.190759	110.1304

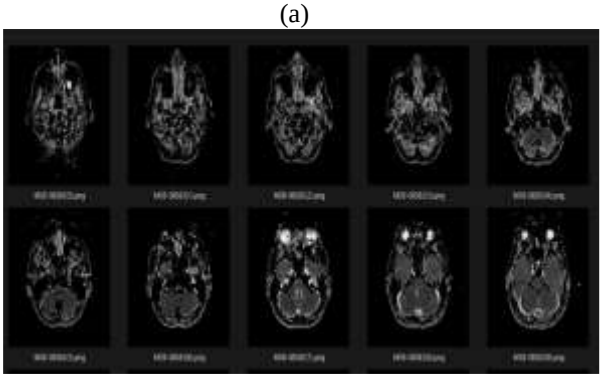
The MRI quality was shown in (a) images before processing with the MRQy software, while (b) images after processing with the software showed a significant difference in image resolution. As show in figure 7. Similar works using deep learning method has been done and reported [18-29].

5. Conclusions

The evaluation of MRI quality across different manufacturers highlighted substantial variations in Signal-to-Noise Ratio (SNR), Contrast-to-Noise Ratio (CNR), and motion-related artifacts, with FBER and EFC metrics indicating distinct levels of motion degradation across SIEMENS, GE, and PHILIPS scanners. Participant-level assessments further revealed disparities in image quality, where a subset of scans demonstrated lower IQM scores, signifying increased noise levels and reduced diagnostic reliability. The integration of MRQy as an automated MRI quality control tool enabled the analysis of 21 MRI datasets within 54.22 minutes, proving its efficiency in assessing and categorizations based on quality. Utilizing machine learning models, particularly Random Forest classification,

the system successfully predicted MRI scan quality with an 80% accuracy rate, reinforcing the significance of SNR, CNR, and FBER as key quality determinants. The implementation of clustering techniques (K-Means, DBSCAN) facilitated the identification of high- and low-quality scans, offering a structured approach to MRI quality classification. These findings emphasize the importance of standardized imaging protocols, ensuring reproducibility across multi-site datasets and fostering reliability in AI-driven diagnostic applications. By integrating automated quality control mechanisms and AI-based quality assessments, future MRI workflows can enhance image consistency, minimize diagnostic errors, and improve patient outcomes, ultimately advancing the field of AI-assisted medical imaging and precision diagnostics.

(a)



(b)

Figure 7. *(a) images before processing with the MRQy software, while (b) images after processing with the software showed a significant difference in image resolution.*

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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