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PAPER

Algorithm-Based Selection of MRI Images to Support Medical Education and Cognitive Skill Development

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ABSTRACT

The study developed and applied a computational algorithm that selects the best medical images, aiming to improve pattern recognition skills among medical students and professionals. The algorithm, written in MATLAB, uses six quantitative metrics—sharpness, contrast, brightness, entropy, processing time, and structural artifacts—and is applied to physiological or pathological magnetic resonance neuroimaging to identify the image that most contributes to improving the visual and diagnostic performance of groups of participants. This is achieved through combinatorial weight analysis (5^6 combinations), in which the image with the highest number of wins is selected. The system was applied to a study with 60 participants divided into three groups (medical students, residents, and specialists in neurology), who answered two questionnaires: the first consisting of raw images selected at random, and the second using images previously processed and selected by the algorithm. The data were statistically analyzed, showing improvement in absolute and relative performance when comparing input and output, with emphasis on the domains of topographic anatomy and zonal recognition of structures. The results indicate that the use of images optimized by objective criteria improves the accuracy of image identification and participant confidence. It is concluded that the use of reproducible and measurable computational solutions is relevant in medical qualification, improving educational and diagnostic performance.

KEYWORDS

medical learning, artificial intelligence (AI), selection algorithm, image processing, performance evaluation

1 INTRODUCTION

Technological progress has fostered strong interaction between health and engineering, particularly in medical physics, bioengineering, and biomedical engineering [1]–[3]. However, despite advances in translational research, technological education in medicine remains limited, with insufficient integration into training programs [4], [5]. Artificial intelligence (AI), especially machine learning and deep learning,

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has become central to medical applications, including large language models, chatbots, and diagnostic support systems based on artificial neural networks (ANNs) [6]–[8]. These tools have reduced diagnostic errors and improved image pattern recognition, particularly in radiology, pathology, pharmacology, and clinical care, contributing to more accurate diagnoses and better outcomes [9]–[15].

Comparatively little attention has been devoted to technologies aimed at enhancing physicians' learning and diagnostic skills [16], [17]. Strengthening medical training is crucial for improving care in chronic and acute diseases [18], [19]. Medical education has increasingly incorporated active methodologies, simulations, and integrated laboratories to foster analytical reasoning [20]–[23]. Nonetheless, image recognition remains a complex skill often underestimated outside radiology, justifying the growing interest in AI support [3], [24].

Educational paradigms that combine medicine, engineering, and education may yield significant benefits [25], especially when inspired by machine learning approaches, where repetition and pre-processing enhance pattern recognition [6]–[8]. Using representative "model" images can help professionals practice recognition of physiological and pathological patterns, especially when aligned with computational tools that assess performance [25], [26]. This study investigates how the selection of optimized medical images can support learning and diagnostic accuracy. We developed a Matlab algorithm ("selectBestImage") that identifies the most representative image from a database using six parameters—contrast, sharpness, brightness, entropy, processing time, and structural artifact estimates. The algorithm was applied in questionnaires with medical students, neurology residents, and specialists, allowing comparison of performance before and after image optimization.

This paper is structured as follows: Section 2 details the dataset, algorithm, image filtering and selection, and group recruitment. Section 3 presents the results of entry and exit assessments. Section 4 discusses these findings, and Section 5 concludes with the main insights.

2 METHODOLOGY

This section describes the technical resources used to design the best image selection algorithm developed for this study. It includes the definition of metrics, weighting parameters, and cross-referencing strategies used to classify and rank candidate images from the database (physiological and pathological). The preprocessing steps (Gaussian filtering and sharpening) applied to enhance images for the output questionnaire are also presented. Finally, we describe the recruitment of research groups, the design of problem-based questions, and their knowledge domains in neuroimaging.

2.1 Algorithm development/definition parameters

An algorithm was implemented in Matlab (R2023b) to objectively select the most appropriate image from a dataset containing diagnostically equivalent representations. The algorithm systematically evaluates a folder of candidate images in PNG or JPEG format, producing a composite score based on six quantitative metrics: contrast, sharpness, brightness, entropy, processing time, and structural artifact estimates (refer to Table 1).

Each image undergoes preprocessing, which includes validation of the input folder, conversion to grayscale (if RGB), normalization of pixel values to the range [0, 1], and resizing to 256×256 pixels to ensure uniformity. After preprocessing, the metrics in Table 1 are extracted for each image.

Table 1. Metrics and methods of obtaining them

Metrics	Mechanism Algorithm for Obtaining
Contrast	Standard deviation of pixel intensity levels.
Sharpness	Variance of image gradients along axes (x, y).
Brightness	Mean intensity of all pixels.
Entropy (variability)	Indicated by textural complexity and local variability.
Processing (Δt)	Time required for resizing and preparation, serving as an indirect metric of computational cost.
Structural Artifacts	Inverse of the SSIM index between the image and a homogeneous gray reference, representing deviation.

Since no consensus was found in the literature on the optimal ranges or combinations of these parameters [27], the selection process relied on both qualitative and quantitative criteria, supported by normalization. Weights (*w*) were used to adjust the relative importance of each parameter. Initially, all weights were set to 1 and later calibrated through comparison with reference images [28]–[30]. The parameters are defined as follows:

Sharpness ($.w1$) → [0 ~ ∞]

- Qualitative definition: Sharpness refers to the clarity and definition of edges and fine details in an image. A sharp image presents well-defined borders, facilitating the identification of anatomical structures and relevant features. In medical imaging, sharpness is crucial for distinguishing tissues and detecting small anomalies [31]–[33].
- Quantitative definition: In this study, sharpness is measured as the variance of the image gradient, calculated using the partial derivatives Gx and Gy obtained with the *imgradientxy* function:

$$sharpness = var\ .\ (Gx(:)) + var\ .\ (Gy(:)) \tag{1}$$

- Application/Interpretation: Gradient variance indicates sharper images, reflecting more abrupt pixel intensity changes at edges.

* *Weight* ($.w1$): Adjusts the relative importance of sharpness in the finalevaluation. A higher weight increases the relevance of edge definition in the scoring process.

Contrast ($.w2$) → [0 ~ ∞]

- Qualitative definition: Contrast represents the difference in intensity between regions of an image. High contrast improves the perception of structures by highlighting variations in brightness, which facilitates interpretation and diagnostic analysis [34]–[36].
- Quantitative definition: Contrast is computed as the standard deviation of pixel intensities, reflecting the disparity between bright and dark regions:

$$contrast = std2\ .\ (double(image)) \tag{2}$$

- Application/Interpretation: Greater standard deviation corresponds to higher contrast, indicating stronger differentiation of structures.

  * *Weight* (.$w2$): Adjusts the importance of contrast in the overall score. A higher weight emphasizes images with greater intensity differentiation.

Variability/Entropy (.$w3$) → [0 ~ ∞]

- Qualitative definition: Variability refers to the diversity of information within an image. High variability indicates complex structures and richer detail, which are fundamental for learning and diagnostic accuracy. Entropy is used as the variability measure [34], [37].
- Quantitative definition: Variability is calculated using image entropy, which measures pixel-level unpredictability:

$$variability = entropy\ .\ (image) \tag{3}$$

- Application/Interpretation: Higher entropy values correspond to more complex images, with richer textural information.

  * *Weight* (.$w3$): Increases or decreases the contribution of variability to the final image score. A higher weight favors images with greater informational content.

Processing time (Δt) (.$w4$) → [0 ~ ∞]

- Qualitative definition: Refers to the elapsed time for CNN-based classification and system response [38]. In analogy to cognitive tasks, shorter times indicate more efficient processing [39].
- Quantitative definition: Measured in seconds with Matlab's tic/toc, stored as *responseTime* (Eq. 4):

$$responseTime = toc \tag{4}$$

- Application/Interpretation: Lower times denote faster systems. This metric enters negatively in the score (–w4).

  * *Weight* (.$w4$): The response time metric enters the figure of merit with a negative sign (.–w4), as a shorter time is desirable. A higher weight will give more importance to images with shorter response times.

Brightness (.$w5$) → [0 ~ 255]

- Qualitative definition: Represents overall image light intensity. Adequate brightness facilitates interpretation and prevents excessively dark or bright regions [40], [41].
- Quantitative definition: Average pixel intensity (Eq. 5):

$$brightness = mean\ .\ (image(:)) \tag{5}$$

- Application/Interpretation: Higher values indicate lighter images.

  * *Weight* (.$w5$): Adjusts the relative importance of brightness in the final image evaluation, favoring lighter or darker images as desired.

Artifacts (.$w6$) → [0 ~ 1]

- Qualitative definition: Unwanted elements such as noise, compression, or pixelation that compromise image fidelity [32], [36].
- Quantitative definition: Measured by structural dissimilarity with an "ideal image" (Eq. 6):

$$artifacts = 1 - ssim\ .\ (image, idealImage) \tag{6}$$

- Application/Interpretation: Values near 0 represent minimal artifacts. Like processing time, this metric has negative weight (–w6).

  * *Weight* (.$w6$): This weight adjusts the relative importance of the presence of artifacts. Since we want to avoid images with artifacts, the weight (.–w6) should be negative, as is the case with weight related to response time (.–w4).

To ensure robustness and reduce dependence on arbitrary weights, a combinatorial approach evaluates all six parameters. Weights $w1$–$w6$ vary within {0.8,0.9,1.0,1.1,1.2}, generating $5^6 = 15{,}625$ combinations. For each, images are scored using a normalized linear model (Eq. 7):

$$Score = w1\ .\tilde{N} + w2\ .\tilde{C} + w3\ .\tilde{E} - w4\ .\tilde{T} + w5\ .\tilde{B} - w6\ .\tilde{A} \tag{7}$$

Where $\tilde{N}, \tilde{C}, \tilde{E}, \tilde{T}, \tilde{B}, \tilde{A}$ are the min–max normalized values of sharpness, contrast, variability, response time, brightness, and artifacts, respectively. The image with the highest score in each iteration earns a "win." The final selection corresponds to the image with the greatest number of wins, ensuring neutrality against weight sensitivity. The algorithm outputs (i) the winning image (.png), (ii) a.txt ranking of wins, (iii) a bar chart of win distribution, (iv) an .xls spreadsheet with results, and (v) an iterative .html report. All files are stored in the result directory within the original dataset. Figure 1 illustrates the functional flow and selection process.

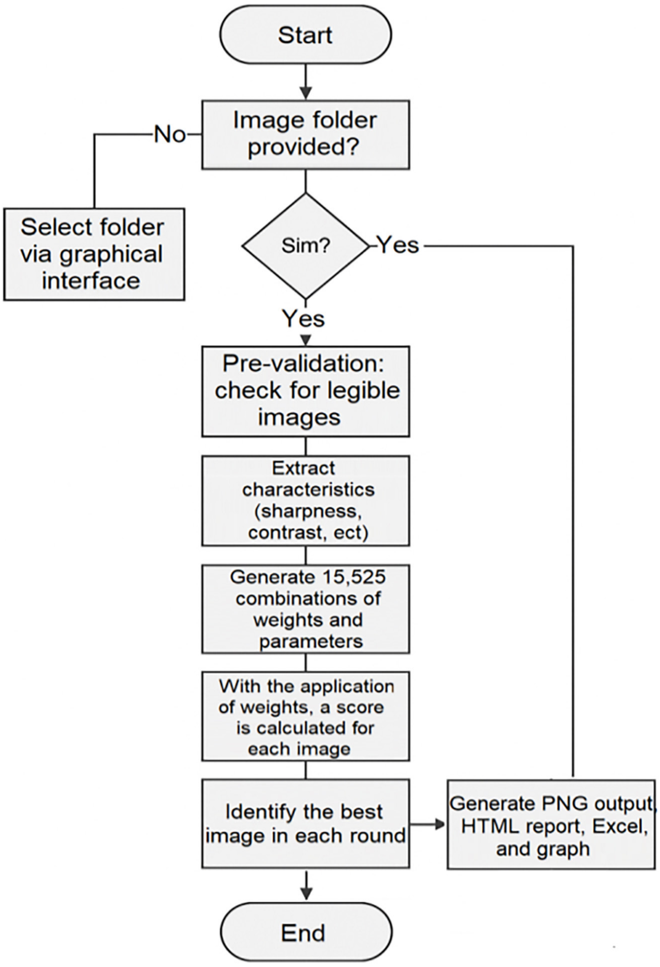


Fig. 1. Image selection algorithm

2.2 Image acquisition and preprocessing

The image databases used in this study, from which physiological (healthy) and pathological (diseased) neuroimages were extracted, were assembled by the researchers. Images were randomly selected for the input questionnaires, while the selection algorithm defined the output questionnaires. A total of 200 images were included, with a balanced distribution between groups.

The healthy neuroimages (n = 50), obtained from MRI scans of different patients, were sourced from the intranet repository of the Neuroimaging Laboratory at the State University of Campinas (opinion number 3,657,509), with images previously reported in the literature [42–45]. The pathological neuroimages (n = 150) were selected from two open-access databases [46–48], covering conditions commonly described in the literature and frequently encountered in clinical practice [44]–[46]. The dataset included MRI scans from distinct patients diagnosed with cerebellar disease/Chiari malformation (n = 50), cortical disease/Alzheimer's (n = 50), and brainstem disease/glioma (n = 50) [43].

For preprocessing, images in the input questionnaires were resized to 256×256 pixels [49]–[51], renamed sequentially (1–50), and stored in separate folders (physiological or corresponding pathology). Image selection for each question was performed randomly. For the output questionnaires, images underwent the same resizing and renaming procedures, followed by normalization to the [0, 1] interval and enhancement with a Gaussian filter (*fspecial('gaussian', filterSize, sigma)*) and a sharpening filter (*imsharpen*) [46]. Selection for these questionnaires was automated by the image selection algorithm, which identified the "winning" physiological and pathological neuroimages to compose the final set of questions.

All included images were appropriate for the study: none were artificially modified (e.g., translated, rotated, blurred) or representative of unrelated conditions. Examples of images used in the input (a) and output (b) questionnaires are shown in Figure 2.

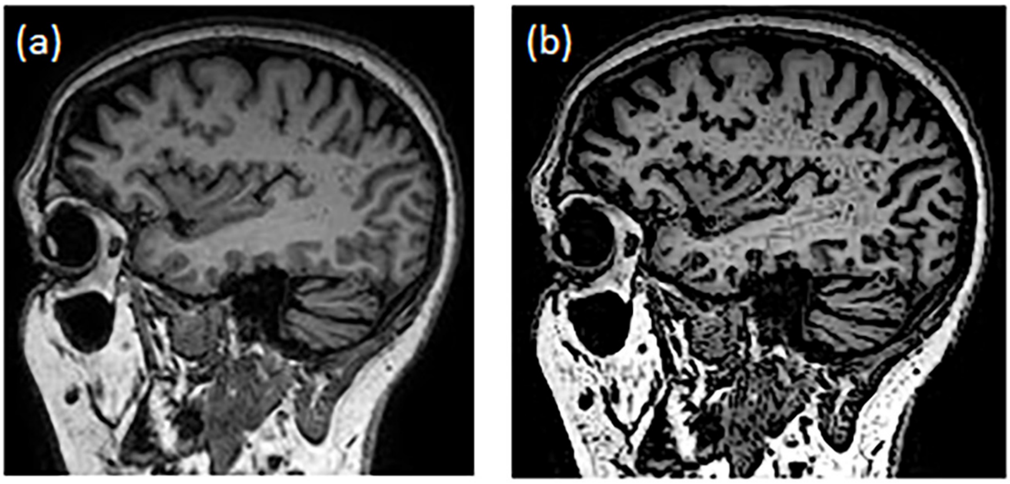


Fig. 2. Images: (a) before and (b) after preprocessing

All images were appropriate (no images were added that were translated, rotated, blurred, or representative of other conditions/types that did not correspond to the study). Examples of images composed in the databases for extraction to the entry (a) and exit (b) questionnaires can be seen in Figure 2.

2.3 Recruitment of research groups

The sample sought to select 60 participants, divided into three groups, representing different levels of knowledge about the analysis of healthy and diseased neurological medical images using MRI, namely 40 medical students who had previously passed a neurology course; 10 general practitioners and postgraduate students in a neurology residency program; and finally, 10 neurologists, professors in the discipline, and active in clinical practice in the specialty. All participants accepted the informed consent form (ICF) prior to being presented with the entry and exit questionnaires. All procedures were reviewed and approved by the Institutional Ethics Committee under opinion number 6,097,741.

2.4 Preparation and application of research questions

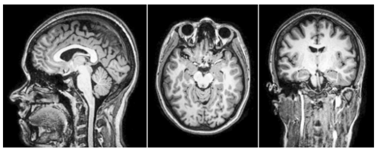
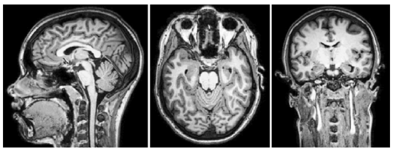
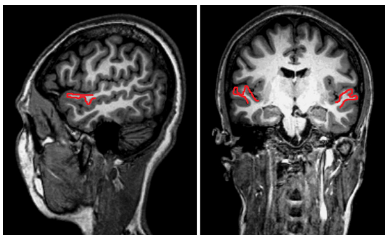
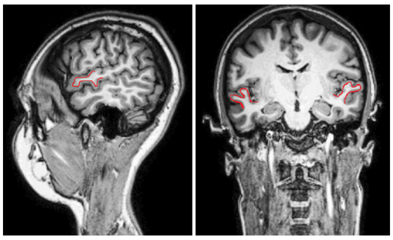
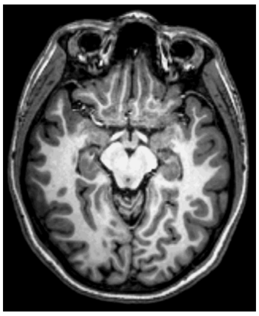
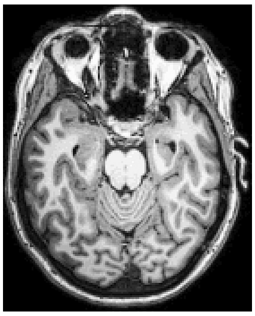
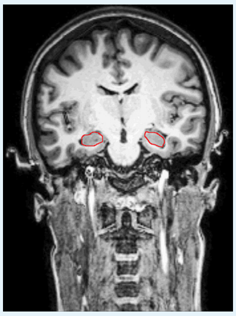
The development of the research questions was carried out with the support of a neuroradiologist, ensuring that each question was adapted to the specific level of knowledge of the target group. This tailoring considered both the academic training of the participants and the practical demands of neuroimaging interpretation in routine diagnostic practice. In this context, the knowledge, reasoning, and technical skills required of medical students, residents, and specialists are directly linked to their ability to provide patient-centered care and to achieve diagnostic accuracy in a timely manner [52]–[54]. Accordingly, the design of structured questionnaires serves as an important diagnostic-educational tool, promoting assimilation of knowledge and fostering continuous improvement of medical reasoning. This approach is aligned with active learning methodologies and continuing education practices, which have been shown to strengthen professional development [8]. Within a translational framework at the intersection of medicine, engineering, and education, analytical learning based on “domains of knowledge” supports accurate, efficient, and time-optimized diagnostic decision-making [55]–[57].

Measuring image recognition across knowledge domains not only integrates image interpretation with clinical problem-solving but also enables the identification of knowledge gaps, creating opportunities for reinforcement and professional advancement. In this study, the questions were structured to address four core domains of technical knowledge in neuroimaging analysis, along with an additional question designed to assess perceptual sensitivity. The domains and their respective relationships are presented in Table 2, while the construction of the applied questions is detailed in Table 3.

Table 2. Accuracy analysis standards–domains/questions

Domain 1	Morphofunctional/Anatomophysiological Fundamentals
Domain 2	Structural, Dimensional, and Volumetric Recognition
Domain 3	Densities, Signals, and Zonal Detections
Domain 4	Topography of Points, Sectors, and Planimetrics
Domain 5	Conscious Understanding and Performance Perspective

Table 3. Applied questions for human research groups

Question	Group	Statement	Entry Questionnaire	Exit Questionnaire
Question 1	Students Residents Specialists	*Is the image representatitve of a physiological (normal) presentation?* **a)** Yes (correct) **b)** No		
Question 2	Students Residents Specialists	*Which anatomical region is affected? If classified as physiological, indicate "not applicable".* **a)** Not Applicable (correct) **b)** *Prefrontal cortex* **c)** *Cerebellum* **d)** Bulb	* This question does not include a new image; it refers back to the image shown in Question 1.	
Question 3	Students	*Which gyre is located in the demarcated area and to which lobe does it belong?* **a)** Superior/Temporary (correct) **b)** Median and Occipital **c)** Median and Frontal **d)** Lower and Insular		
	Residents Specialists	*Looking at the "substantianigra," what is its signal intensity when compared to the "cerebral peduncles"?* **a)** It's Hypointense (correct) **b)** It's Hyperintense **c)** They are isointense. **d)** There is no relationship between intensities		
Question 4	Students Residents	*Which neurological system does the marked image belong to?* **a)** Hippocampus (correct) **b)** Hypothalamus **c)** Substantia Nigra **d)** Amygdala		
	Specialists	*Indicate which anatomical structure is compromised and the pathology.* **a)** Cerebellum/Chiari (correct) **b)** Brainstem/Glioma **c)** Cortex/Dementia **d)** Not Applicable		

2.5 Data analysis

The responses obtained before and after the intervention were tabulated in Excel and analyzed descriptively through absolute and relative frequencies, represented graphically. The relationship between the number of correct answers per group and the knowledge level was examined using the chi-square test (X^2), with bivariate analysis at a 5% significance level. In addition to this, the results obtained by the research groups will be discussed through absolute (8) and relative (9) growth.

$$\text{C.A} = \textit{final value} - \textit{initial value} \tag{8}$$

$$\text{C.R} = \left(\frac{\textit{Final Value} - \textit{Initial Value}}{\textit{Initial Value}}\right) \times 100 \tag{9}$$

3 RESULTS

The analysis considered both questionnaire applications. Tables 4 and 5 present the distribution of correct and incorrect responses for questions 1 and 2, before (a) and after (b) the intervention.

For Question/Domain 1 ("Morphofunctional/Anatomical-Physiological Conformational Fundamentals"), no statistically significant association was observed between knowledge level and correct responses, either before ($p = 0.8136$) or after ($p = 0.7137$) the intervention. For Question/Domain 2, the chi-square test also indicated no significant associations ($p > 0.05$), despite the descriptive increase in correct responses across all groups after the intervention.

Table 4. Accuracy by research group–question 1

Question/Domain 1	***Correct (%)**		**Incorrect (%)**		**Difference in Hits**
	Before	**After**	**Before**	**After**	
Students	41,18	58,82	58,82	41,18	**↑ 17,64%**
Residents	30,00	70,00	70,00	30,00	**↑ 40,00%**
Specialists	40,00	70,00	60,00	30,00	**↑ 40,00%**

Table 5. Accuracy by research group–question 2

Question/Domain 2	***Correct (%)**		**Incorrect (%)**		**Incorrect (%)**		**Incorrect (%)**		**Difference in Hits**
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	
Students	38,24	58,82	50,00	17,65	8,82	8,82	2,94	14,71	**↑ 20,58%**
Residents	50,00	80,00	30,00	10,00	20,00	10,00	0,00	0,00	**↑ 30,00%**
Specialists	50,00	80,00	30,00	0,00	0,00	10,00	20,00	10,00	**↑ 30,00%**

Question/Domain 3 ("Performance of Densities / Signals and / or Zonal Detections") also showed no statistical significance ($p > 0.05$), with $p = 0.7793$ in the entry questionnaire and non-significant results in the exit assessment (Tables 6 and 7).

In contrast, Question/Domain 4 ("Topographic Points, Sectors, Neurodelimitations Planaltimétricas") revealed statistical significance at entry (p = 0.0462), suggesting an association between training level and response accuracy. At exit, however, significance was not sustained (p = 0.0571). Finally, Question/Domain 5 ("Conscious Understanding and Performance Perspective") did not present statistical significance at either moment (p > 0.05).

Table 6. Accuracy by research group–question 3

Question/Domain 3	*Correct (%)		Incorrect (%)		Incorrect (%)		Incorrect (%)		Difference in Hits
	Before	After	Before	After	Before	After	Before	After	
Students	38,24	44,12	32,35	29,41	17,65	8,82	11,76	17,65	↑ 5,88%
Residents	50,00	70,00	30,00	10,00	10,00	20,00	10,00	0,00	↑ 20,00%
Specialists	60,00	80,00	30,00	10,00	10,00	10,00	0,00	0,00	↑ 20,00%

Table 7. Accuracy by research group – question 4

Question/Domain 4	*Correct (%)		Incorrect (%)		Incorrect (%)		Incorrect (%)		Difference in Hits
	Before	After	Before	After	Before	After	Before	After	
Students	26,47	41,17	5,88	14,71	20,59	5,88	47,06	38,24	↑ 14,70%
Residents	80,00	90,00	0,00	0,00	0,00	0,00	20,00	10,00	↑ 10,00%
Specialists	80,00	100,0	10,00	0,00	0,00	0,00	10,00	0,00	↑ 20,00%

Analyzing the absolute and relative growths, for question 1, undergraduate students showed absolute growth of 17.64% and relative growth of 42.84%, while residents expressed absolute growth of 40% and relative growth > 130% (133.33%) in their ability to answer correctly, and specialists showed absolute growth of 40% and relative growth of 75%, as shown in Figure 3.

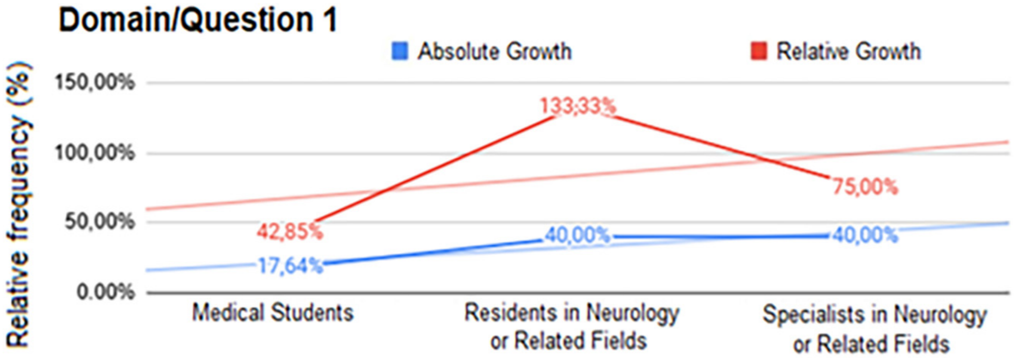


Fig. 3. Absolute and relative growth in groups–question 1

Regarding question 2, undergraduate students showed absolute growth of 20.58% and relative growth of 53.82%, while residents and specialists showed absolute growth of 30% and relative growth of 60%, respectively. Compared to the previous question, there is greater uniformity among the groups in the improvement of their answers, as can be seen in Figure 4.

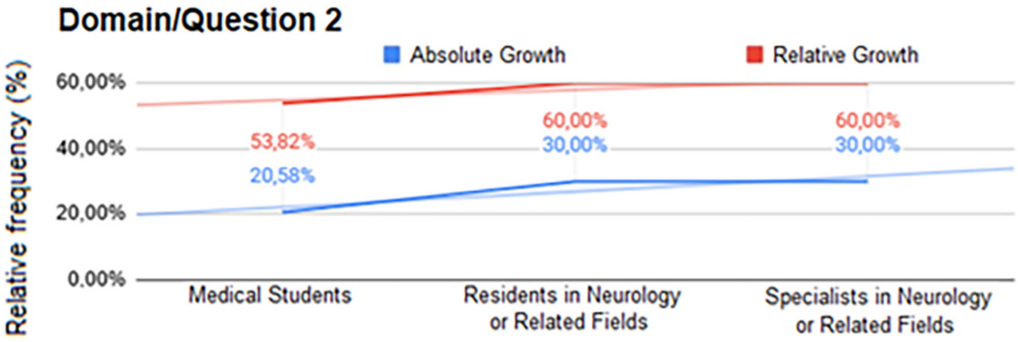


Fig. 4. Absolute and relative growth in groups–question 2

In question 3, undergraduate students showed absolute growth of 5.88% and relative growth of 15.38%, while residents and specialists showed absolute growth of 20% and relative growth of 40.00% and 33.33%, respectively. Compared to the previous question, undergraduate students continued to show improvement, albeit less intense than residents and specialists, who maintained similar growth (see Figure 5).

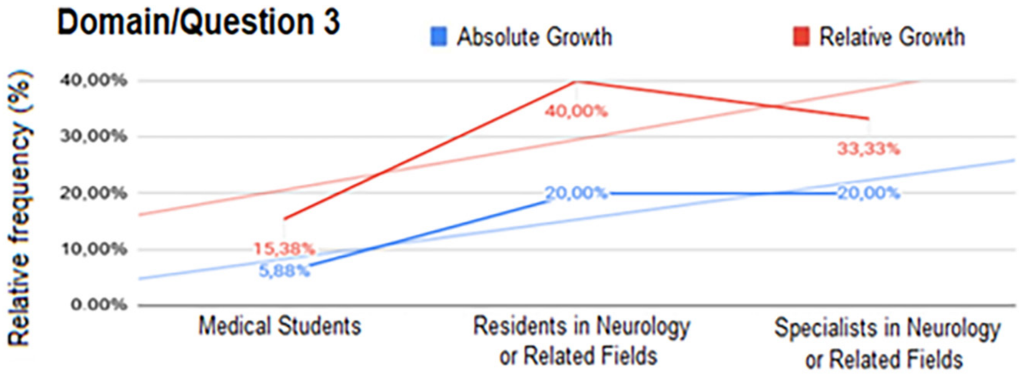


Fig. 5. Absolute and relative growth in groups–question 3

Comparing question 4, undergraduate students showed absolute growth of 14.71% and relative growth of 55.57%, while residents and specialists showed a more subtle difference between both growth rates, with absolute growth of 10% and 20% and relative growth of 12.50% and 25.00%, respectively. Comparing the other questions, undergraduate students showed quite significant relative growth when compared to the other groups, as can be seen in Figure 6.

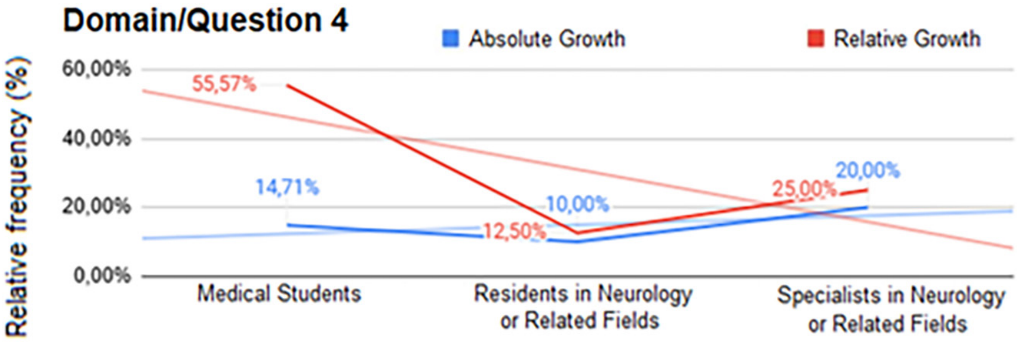


Fig. 6. Absolute and relative growth in groups–question 4

Finally, regarding the issue of sensitivity and impressions when answering the questionnaires, observed in domain 5, it can be seen in Figure 7a, before, and Figure 7b, after, for comparison between the first and second applications, showing a reduction in the indication of difficulty and an increase in the perception of ease when answering. The change in this expression is consistent with the increase in correct answers.

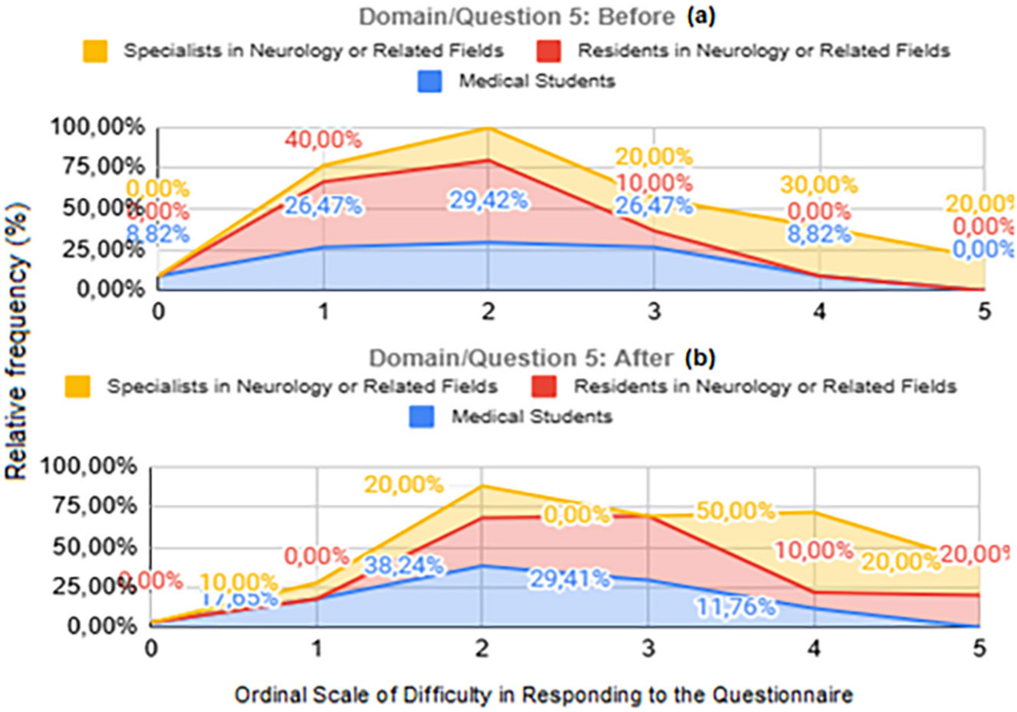


Fig. 7. Sensitivity and impression when responding–question 5

4 DISCUSSION

The development of the questions in this study required reflection on knowledge assessment and continuous professional improvement, highlighting the importance of tools that not only analyze but also enhance professional skills. Verification instruments should link theory and practice, contextualizing professional dynamics and aligning with labor market demands. In the health and care sector, such demands are increasingly shaped by technological resources [54], [58]. While these resources expand the physician's analytical capacity, they are also accessible to patients, who arrive more informed and critical. Therefore, analytical tools that assess academic and professional accuracy contribute to refining competencies essential to the doctor–patient relationship.

The results showed that in the exit questionnaire, all groups improved in questions 1–4 (techniques), as well as in question 5 (sensitivity), indicating greater ease in image analysis compared to the entry questionnaire. This aligns with studies emphasizing that technological innovation in healthcare must enhance working conditions and professional practice [9], [11], [25], [46], [55]. In this context, medical education bridges technical and conceptual fundamentals with applied resources from medical physics, bioengineering, and biomedical engineering [4], [25], [53]. Active learning, combined with continuous improvement, helps detect and address knowledge gaps [4], [25], [54], supporting more efficient and reproducible medical care [52]. Nonetheless, limitations must be acknowledged. The use of curated images from open databases may introduce clinical bias, reducing representativeness of real-world variability. The structured questions, focused mainly on topographical and structural perception, may omit competencies required for complex clinical contextualization. The scarce literature limits statistical validation, psychometric analysis, and content validity index (CVI). Furthermore, although technically robust, the algorithm may face efficiency issues with large datasets, requiring optimization or parallel processing for large-scale applications. Performance gains observed in some domains were not statistically significant overall, suggesting that isolated interventions are insufficient for lasting improvements, reinforcing the need for longitudinal and integrated approaches.

Despite these challenges, the proposal is promising for competency-based medical education and translational research at the intersection of machine learning, bioengineering, and medical training. Future directions include the following: (i) generalization to other medical specialties with curated image banks; (ii) incorporation of evolutionary algorithms and deep learning for enhanced pattern recognition and adaptive refinement; (iii) integration of longitudinal data (accuracy evolution, recurrence of errors, and response time) to support adaptive learning models; and (iv) multicenter longitudinal validation to ensure heterogeneity and scalability.

5 CONCLUSION

This study evaluated an algorithm capable of automatically selecting MRI images using quantitative metrics derived from visual–qualitative skills. The proposed model proved to be technically robust and methodologically structured, enhancing image selection, accuracy, and neuroimaging perception among medical students and professionals. Although the intervention showed variable impact across knowledge domains—greater in topographic anatomy and zonal detection and less in morphoconational fundamentals—all groups demonstrated absolute and relative improvements in correct responses, as well as gains in sensitivity and subjective perception. These findings suggest a positive relationship between image quality and cognitive performance. Thus, the model demonstrates potential not only as an educational tool but also as a framework for developing adaptive and enriched approaches to medical education.

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