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Original article

An automated measurement of head circumference using CT scans: An application in children with head abnormalities

Priscila Satomi Acamine [a,*], Rafael Maffei Loureiro [b], Lucas dos Anjos Longas [a], Fabio Augusto Ribeiro Dalpra [b], Luigi Villanova Machado de Barros Lago [a], Larissa Vasconcellos de Moraes [a], Paulo Cesar Filho Estevam [a], Luiz Otávio Vittorelli [a], Lucas Silva Kallás [a], Ana Paula Antunes Pascalicchio Bertozzi [c], Maria Isabel Barros Guinle [a,d], Gilberto Szarf [a,b], Saulo Duarte Passos [c], Birajara Soares Machado [a], Joselisa Péres Queiroz De Paiva [a]

[a] Imaging Research Center, Hospital Israelita Albert Einstein (HIAE), Av. Albert Einstein, 627/701 – Morumbi, São Paulo, CEP: 05652-900, SP, Brazil
[b] Department of Radiology, Hospital Israelita Albert Einstein (HIAE), Av. Albert Einstein, 627/701 – Morumbi, São Paulo, CEP: 05652-900, SP, Brazil
[c] Department of Paediatrics, Faculdade de Medicina de Jundiaí, R. Francisco Teles, 250 - Vila Arens II, Jundiaí, CEP: 13202-550, SP, Brazil
[d] Stanford University School of Medicine, Stanford, 291 Campus Drive, Stanford, 94305, CA, United States

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ABSTRACT

Manual measurement of head circumference has been a widely adopted method of neurodevelopmental evaluation in both clinical and research settings. Here, we propose a method that uses axial slices of computerized tomography (CT) scans to detect the largest outer margin for measurement. Our method can both complement conventional tape measurements or be applied as a standalone tool, especially in the context of retrospective big data analysis. We applied our algorithm in a set of 74 head CT scans obtained from individual children (8,5 ± 14,1 months old). The method proved to be concordant ($ICC[2,k] = 0.99$), consistent ($ICC[3,k] = 1$), and showed a correlation of 0.988 compared to obtaining manual head circumferences by specialists. Our method is a reliable alternative to conventional manual measurements of head circumference. It can be readily applied in macrocephaly and microcephaly screening studies and in growth reference charts for syndromes related to head alterations.

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1. Introduction

Measurement of head circumference (HC) is a standard procedure in pediatric patient evaluations [16]. Several studies have shown that abnormal HC values, defined as ≤ -2 or ≥ 2 standard deviations (SD) from the expected range for age and sex, are associated with intellectual delay, epilepsy, cerebral palsy, and other neurological, cognitive, psychomotor and behavioral outcomes [7,8,11,20–22,28]. Some authors have also described a cubic relationship between HC and postmortem brain weight Cooke et al. [5], reinforcing the use of HC as an indirect and accessible estimate of brain volume Serru et al. [21].

Although easy to perform and low-cost, manual HC measurement can vary between raters and even between measurements from the same examiner [1,6,25]. Factors such as head positioning, tape flexibility, and examiner experience influence the outcome, and such variability can affect the interpretation of growth over time. Some studies suggest that measurements taken with non-stretchable tape have higher reproducibility than measurements taken with routine tape Thakkar et al. [25], but this still requires training and standardization. Furthermore, manual measurement is not available in retrospective analyses when only imaging data is accessible.

In situations where physicians suspect brain or skull abnormalities, computed tomography (CT) is frequently used to evaluate structural changes [13]. These CT images, often already available in the hospital system, contain information that can be used to estimate HC, even if that is not the original purpose of the exam. This opens the possibility of using head CT scans as a source for automated HC measurement, which can support both clinical evaluations and large-scale retrospective studies.

In this study, we present an automated method for estimating HC using only axial slices from non-contrast head CT scans. The

* Corresponding author.
E-mail addresses: priscilaacamine@gmail.com, priscila.satomi@einstein.br (P.S. Acamine).

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Table 1
Subjects' characteristics from each validation group.

	Total	Radiological Validation	Clinical Validation
Number of subjects	74	60	14
Sex	F = 41	F = 35	F = 6
	M = 33	M = 25	M = 8
Age range	0 day – 4.55 years	0 day – 4.55 years	2 day – 8.95 months
Mean age (SD)[days]	255.22 (424.37)	284.62 (464.09)	129.21 (112.78)

pipeline performs image preprocessing, aligns the head, filters out unsuitable slices, and calculates the HC based on the largest external contour. We applied this method to a set of 74 pediatric head CTs, including children with normal and abnormal HC (microcephaly and macrocephaly), acquired from four different clinical centers with varying image quality and scanning protocols.

To evaluate the method, we compared the automated HC values with those obtained manually by two board-certified neuroradiologists and, in a separate dataset, with HC measured during in-person pediatric examination using a measuring tape by an experienced pediatrician.

Our aim is not to replace expert evaluation, but to offer a tool that can complement manual HC measurement, particularly useful in retrospective research or in settings where clinical measurements are unavailable or unreliable. We also expect this method to be helpful in studies of growth patterns, rare diseases, and syndromes with cranial morphological changes.

This paper presents a reliable, open-source method to measure head circumference from CT scans and shows its agreement with conventional clinical methods.

2. Methods

2.1. Study population and CT scanning

This retrospective study was approved by the Institutional Ethical Review Board (CAAE 31894220.5.0000.0071), which waived the requirement for written informed consent.

The total sample consisted of de-identified and non-contrast head CT scans acquired from 74 children (41 females and 33 males) with ages ranging from 0 days to 4.55 years (mean $\pm$ SD: 255 $\pm$ 424 days). During data anonymization, we add an equal random integer to each individual's exam acquisition date and date of birth to preserve the difference between dates. The children were either normocephalic or presented with abnormal HC (microcephaly: ≤ -2 SD; macrocephaly: ≥ 2 SD) [18]. Supp. Table 1 shows the participants' demographic characteristics in detail.

We validated against images from 60 individuals (35 females and 25 males) with ages ranging from 0 days to 4.55 years (mean $\pm$ SD: 285 $\pm$ 464 days) who had previously undergone CT scans for various medical reasons: 20 children were normocephalic and 40 had abnormal HCs (31 microcephalic and 9 macrocephalic). To best simulate real-world heterogeneity, we considered CT scans acquired from three different clinical centers (for detailed descriptions of the clinical centers, refer to Supp. Material) with various scanner settings (Supp. Tables 2 and 3), and varying image quality.

To compare our automated HC measurements to HC measurements collected with a measuring tape, we obtained an additional CT dataset from another institution (Hospital Universitário de Jundiaí; Supp. Material) of 14 pediatric patients (10 normocephalic and 4 microcephalic), who were members of a high-risk pregnancy and birth cohort [4]. This clinical validation sample consisted head CT scans acquired from 14 children (6 females and 8 males) with ages ranging from 2 days to 8.95 months (mean $\pm$ SD: 129 $\pm$ 113 days). Table 1 shows the participants' demographic characteristics for each validation group.

2.2. Head circumference measurement

To measure head circumference, our algorithm identified the image contours in each axial slice, extracted the total pixels from the outermost contours, and converted pixels to centimeters. We then compared HC values across axial slices and identified the largest HC measurement.t. See Fig. 1. for the pipeline flowchart.

Prior to measuring head circumference, we ran the input image through an automated preprocessing pipeline: The image was oriented according to radiological conventions (left-anterior-superior), and we extracted the head, removing external artifacts, with binary masking (for more details, see Supp. Material).

To align the head, we first resized a publicly available CT template, including the brain and skull, [19] to the voxel dimensions of the input image. We did an initial similarity transform, using the SimpleITK library [15], between the fixed (resized template) and moving images to estimate the quaternions, translation, and center parameters used to rotate and translate the CT image on the template. We also included the size, origin, pixel spacing and direction of each image. These parameters were then used in a rigid registration. Since similarity metric computation was non-deterministic [23], we repeated these steps until convergence, outputting the final head-aligned image (for more details, see Supp. Material). The alignment step of the pipeline requires a CT image file with at least 20 slices.

To generate a binary head mask, we discarded 30% of the upper and 40% of the lower slices to avoid unwanted regions (e.g., eyes, ears, and nose); applied a lower threshold filter of -150 HU to highlight head and skin structures; selected the largest segment; and performed an open operation (see Supp. Material). Alternatively, a different threshold can be applied to the preprocessed images to highlight bone structures such as the skull (60 HU), which allows the skull to be treated as the outermost contour. However, since there are no known reference values for skull circumferences to date, we restricted data analysis to a threshold filter that includes skin structures. We used non-contrast brain window CT images; however, this method can be also used for head CT scans acquired with contrast and/or those shown in the bone window. Fig. 2A presents the aligned image after preprocessing and Fig. 2B a comparison of the HC to a reference table [18].

2.3. Statistical analysis

2.3.1. Repeatability and reliability

Due to our method's nondeterminism, we assessed repeatability by measuring the HC of all individuals from the primary dataset ($n = 60$) three times, like [25], and compared variations in measurements.

The data were analyzed using one-way repeated-measures ANOVA to investigate changes in the mean HC measurements over each execution of the algorithm, excluding the influence of subjects' intrinsic differences. To evaluate the reliability of our HC measurements, we calculated the intraclass correlation coefficient (ICC) for a single rater for both absolute agreement (ICC[2,1]) and consistency (ICC[3,1]). Finally, we assessed the variability among the repeated measurements of each subject by using the coefficient of variation (CV).

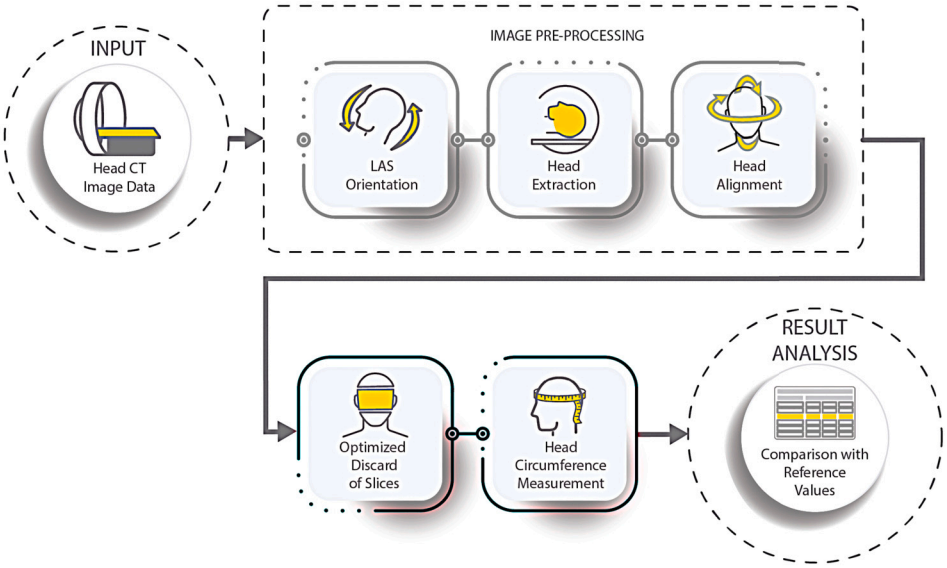

Fig. 1. Head Circumference analysis pipeline. Our algorithm uses the head CT image as input. First, the image preprocessing consists of the following steps: LAS (left-anterior-superior) orientation, head extraction, and head alignment. Then, an optimized process for discarding slices is performed, and head circumference is measured from the largest slice of the head. Finally, the measured head circumference value should be compared with child growth standards reference values based on the individual's sex and age.

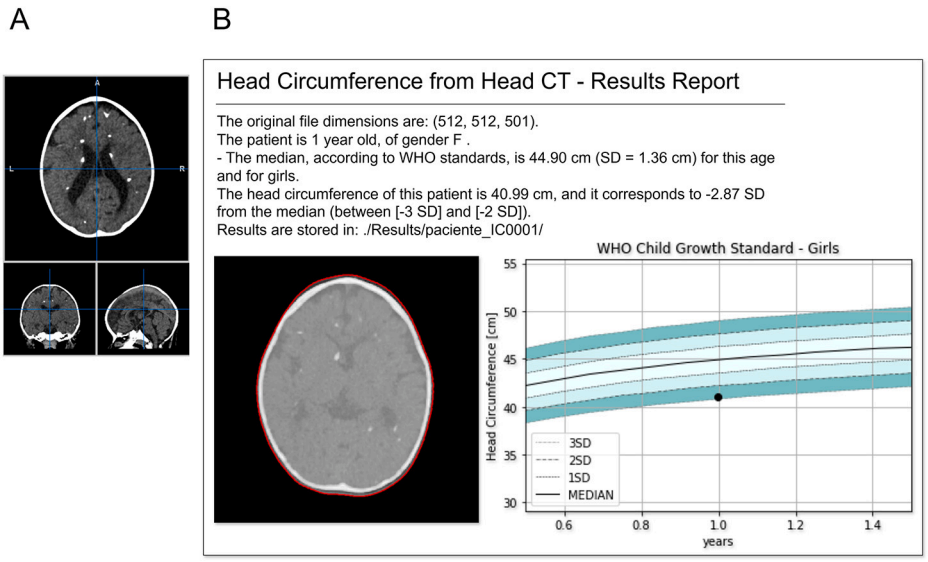

Fig. 2. Representative results from our Head Circumference pipeline. (A) Image after preprocessing (head alignment). (B) Example of a result report containing relevant information about the subject; standard growth chart according to sex and age depicting the individual's actual HC value; and image of the largest axial slice of the head (the HC is outlined in red).

We also verified the preservation of both the image dimensions and voxel spacing by evaluating the parameters before and after the pipeline.

2.3.2. Radiological measurement validation

To validate our results, two experienced neuroradiologists (RML and FARD), both with more than seven years of experience, manually measured the HC for all individuals in the primary dataset ($n = 60$). Using DICOM viewer software (RadiAnt, Poznan, Poland), HC measurements were obtained using a closed polygon tool, delimiting the contour around the presumably widest circumference of the head, including the broadest part of the frontal region and the most prominent part of the occipital region. Also, the radiologists reconstructed the images in the axial plane in a manner analogous to the clinical measurement to identify the image slice with the largest circumference.

The average of three automated HC measurements from the CT scan (HC_{mean}) was compared to the measurements obtained by the two neuroradiologists (RAD_1 and RAD_2), using a one-way repeated measures ANOVA. We then determined the ICC value for multiple raters, ICC[2, k] and ICC[3, k]. The HC_{mean} was compared separately to the measurements obtained by each neuroradiologists by using Spearman correlation analysis, mean absolute error values, and the Bland-Altman plot [2]. The head alignment was analyzed qualitatively by the neuroradiologists.

2.3.3. Clinical measurement validation

For this validation, we used the secondary dataset ($n = 14$) and compared the HCs obtained by our pipeline to the HC measurements taken by an experienced physician (SDP), with more than thirty years of experience as a pediatrician, using a non-elastic tape measure held above the eyebrows and ears, in accordance with WHO recommendations. Both manual HC and CT scans used

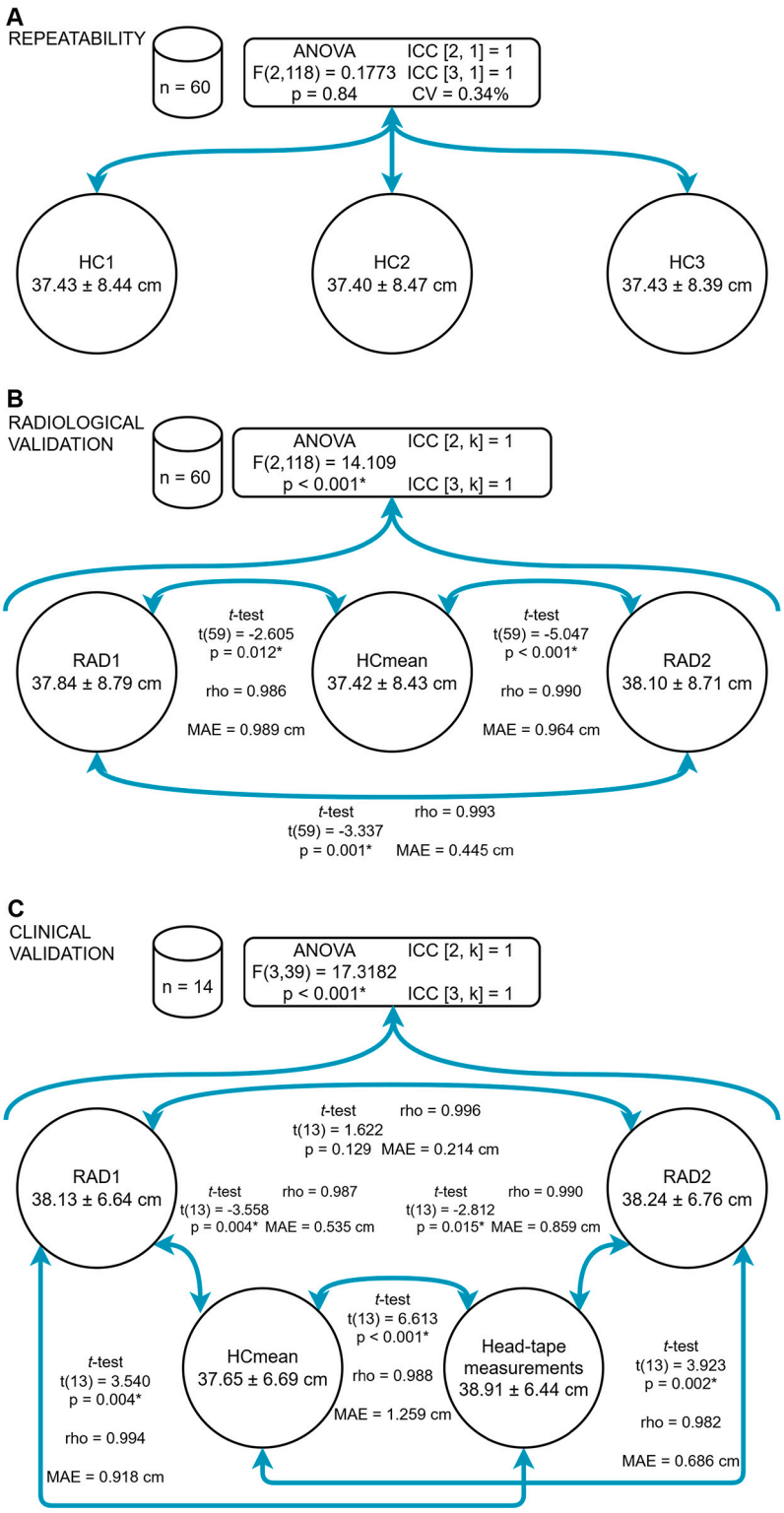

Fig. 3. Statistical analysis for (A) Repeatability, (B) Radiological Validation, and (C) Clinical Validation. In the upper plot (A), HC_1, HC_2 and HC_3 are the first, second and third trials of automated HC measure, respectively. In plots (B) and (C), RAD_1 and RAD_2 denote the HC measured by neuroradiologists and HC_{mean} is the average of three serial automated HC measures. $*$ denotes statistical significance at $p < 0.05$.

here came from a prospective study [4]. To ensure that the comparison was not compromised by the individual's head growth over time, we selected patients whose CT acquisition and clinical assessment were performed no more than 7 days apart.

In the same way as described in Sec. 2.3.2, the neuroradiologists manually measured the HC for the individuals in the secondary dataset. The HC_{mean} and the measurements obtained RAD_1 and RAD_2 were compared to the HC measured by the pediatrician in clinical practice using a one-way repeated measures ANOVA and the ICC value for multiple raters, ICC$[2, k]$ and ICC$[3, k]$. Each rater's measurements were compared separately to the measurements obtained by the pediatrician by using Spearman correlation analysis, mean absolute error values, and the Bland-Altman plot [2].

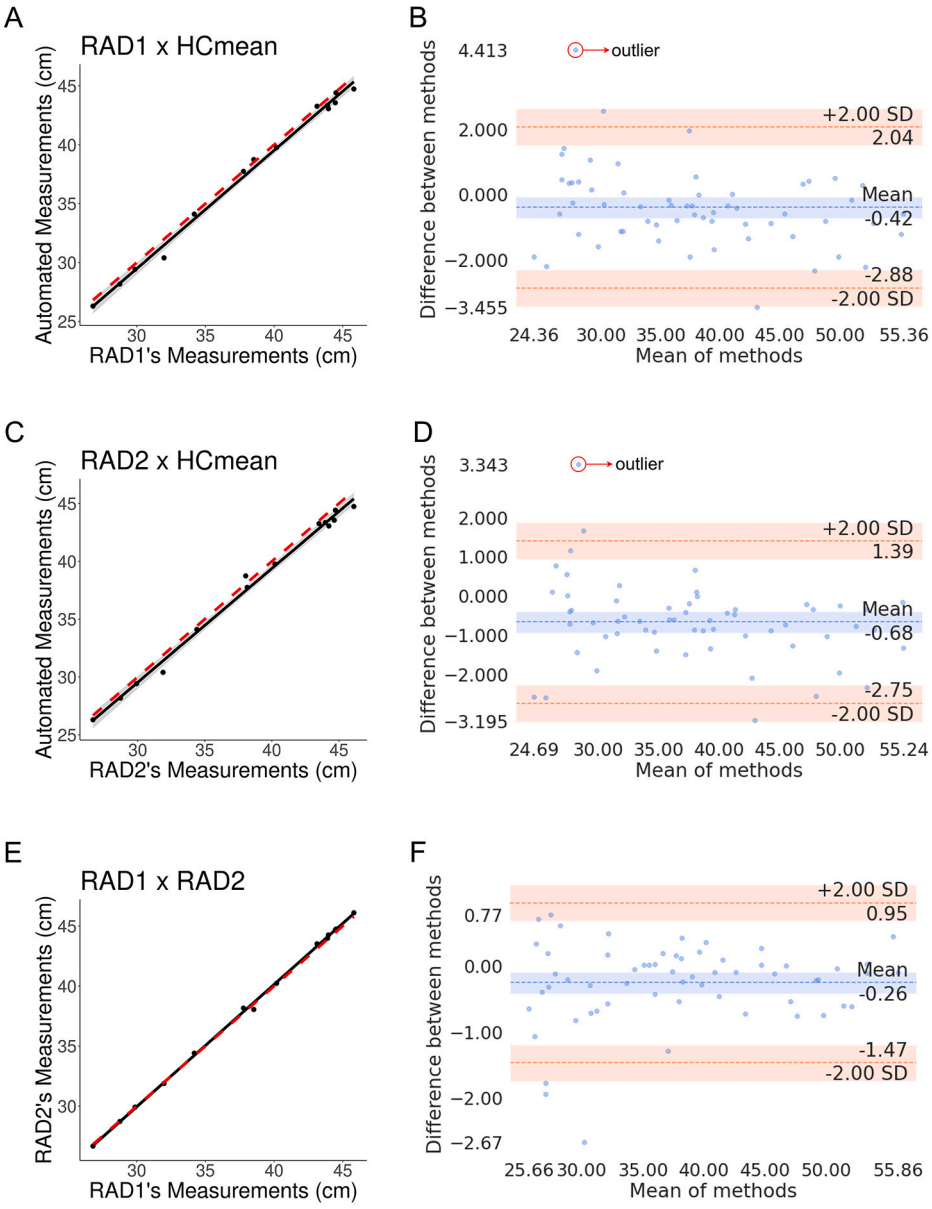

Fig. 4. (A) Dispersion plot for HC_{mean} vs. RAD_1. (B) Bland-Altman plot for HC_{mean} vs. RAD_1. (C) Dispersion plot for HC_{mean} vs. RAD_2. (D) Bland-Altman plot for HC_{mean} vs. RAD_2. (E) Dispersion plot for RAD_1 vs. RAD_2. (F) Bland-Altman plot for RAD_1 vs. RAD_2. Bland-Altman plots use 95% confidence intervals for the mean difference according to Student's t Table. The outlier is highlighted in red for HC_{mean} vs. RAD_1 and RAD_2. We observe 3 outliers in (F). RAD_1 and RAD_2 denote the HC measured by neuroradiologists and HC_{mean} is the average of three serial automated HC measures. The red dashed line on (A), (C) and (E) represents the maximum correlation.

3. Results

To evaluate the consistency of the proposed method, we repeated the head circumference calculation three times, due to the non-determinism of our method. In this way, we obtained the three consecutive HC evaluations (HC_1 = 37.43 ± 8.44 cm; HC_2 = 37.40 ± 8.47 cm; HC_3 = 37.43 ± 8.39 cm) for the same dataset (the primary dataset with $n = 60$ subjects). No significant differences ($F(2, 118) = 0.1773$, $p = 0.84$) were observed among the three replications of HC measures considering a one-way repeated measures ANOVA. Moreover, the three HC measure replications were highly concordant (ICC [2,1] = 1) and consistent (ICC [3,1] = 1), with low variation – the mean coefficient of variation (from the 60 subjects) was $\overline{CV} = 0.34\%$ and the observed standard deviation was $SD_{CV} = 0.69\%$. These results support the repeatability and reliability properties of our proposed method and are schematized in Fig. 3A.

Validating these methods with radiological measurements, we propose a comparison of multiple samples for repeated measurements considering measurements done by radiologists and a mean of three measurements using our method. There was a significant difference between HC_{mean}, RAD_1 and RAD_2 ($F(2, 118) = 14.109$, $p < 0.001$) evidenced by the ANOVA and post-hoc pairwise t-test (illustrated in Fig. 3B). Although manual HC measurement from a brain CT scan is not a common practice for radiologists, to our knowledge, this is the first study to address the interobserver measurement variability. The significant differences between RAD_1 (37.84 ± 8.79 cm) and RAD_2 (38.10 ± 8.71 cm) mean measurements ($t(59) = -3.337$, $p = 0.001$) might reflect the fact that the head CT plane selected as presumably the largest is based on subjective evaluation, eventually resulting in different plans chosen by the radiologists. A sensitivity due to the choice of slice is also noted and becomes evident when comparing HC_{mean} (37.42

Table 2
Mean difference in head circumference measures between methods and their respective agreement according to the SD of the head circumference for age. For the radiological validation the mean age of the subjects was 9.5 months, which corresponds to the SD of 1.3019 cm; for the clinical validation, the mean age was 4.3 months, which corresponds to the SD of 1.2349 cm. The SD_{HC} was obtained based on the proportionality between the SD reference values of the adjacent complete ages available in the WHO table [18] and a simple average was made between the values for each sex.

Method	Sample size	Mean Bias, cm	Limits of Agreement		SD_{HC}(9.5 months) = 1.3019 cm		
			Lower, cm	Upper, cm	Underestimated *n* (%)	Overestimated *n* (%)	Agreement *n* (%)
$HC_{mean} - RAD_1$	60	−0.42	−2.88	2.04	11 (18.33)	4 (6.66)	45 (75)
$HC_{mean} - RAD_2$	60	−0.68	−2.75	1.39	13 (21.66)	2 (3.33)	45 (75)
$RAD_1 - RAD_2$	60	−0.26	−1.47	0.95	3 (5)	0 (0)	57 (95)
Method	Sample size	Mean Bias, cm	Limits of Agreement		SD_{HC}(4.3 months) = 1.2349 cm		
			Lower, cm	Upper, cm	Underestimated *n* (%)	Overestimated *n* (%)	Agreement *n* (%)
HC_{mean}-Head Tape	14	−1.26	−2.73	0.21	7 (50)	0 (0)	7 (50)
RAD_1-Head Tape	14	−0.78	−2.47	0.92	3 (21.43)	0 (0)	11 (78.57)
RAD_2-Head Tape	14	−0.67	−2.52	1.18	5 (35.71)	0 (0)	9 (64.29)

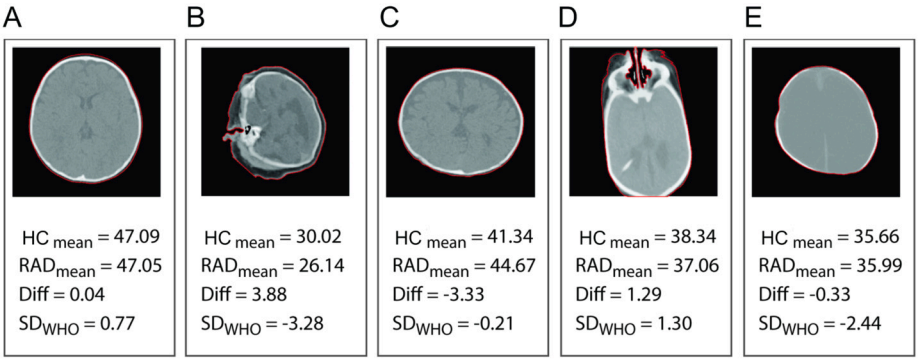

Fig. 5. Representative results using our head circumference (HC) algorithm. (A) Good performance in a normocephalic case. (B) Poor performance in outlier (Figs. 4B and 4D): the algorithm incorrectly included a part of the right ear, orbit, and temporo-occipital skin in the largest selected slice. (C) Poor performance, underestimating HC. (D) In this case of poor performance, the largest slice contour included the orbits and nose. (E) A case of mismatch between assessments performed by our algorithm and radiologists: a patient with ventriculomegaly was classified as microcephalic by our algorithm but wrongly labeled as severely macrocephalic in radiologists' qualitative evaluation. HC_{mean} is the average of three serial automated HC measures; RAD_{mean} is the mean HC measured by the two neuroradiologists; Diff is the difference between measures (Diff = HC_{mean} − RAD_{mean}); SD_{who} is the correspondent standard deviation of the HC_{mean} according to World Health Organization's Child Growth Standards, by sex and age.

± 8.43 cm) with RAD_1 ($t(59) = -2.605$, $p = 0.012$) and RAD_2 ($t(59) = -5.047$, $p < 0.001$).

However, HC_{mean} and RAD measurements were highly concordant (ICC[2, *k*] = 1), consistent (ICC[3, *k*] = 1), and correlated ($rho = 0.986$ for RAD_1 and 0.990 for RAD_2), as shown in Figs. 4A and 4C. The mean absolute error (MAE) was 0.989 cm and 0.964 cm between HC_{mean} and RAD_1 and RAD_2, respectively. Fig. 3B summarizes the statistical analysis for radiological validation. Despite the random nature of the choice of slice and the observer bias pointing to a mean difference across observers, the behavior and interpretation of these measurements are valid. Their validity is evidenced by measures of concordance and consistency, especially when considering their use in the context of comparing images.

The Bland–Altman plot (see Figs. 4B and 4D) revealed that our proposed method tends to underestimate HC compared to radiologists. A bias of −0.42 cm and −0.68 cm was found between RAD_1 and RAD_2, respectively (Table 2). In addition, the degree of downward bias increases with head size (Figs. 4A and 4C). An outlier (Figs. 4B, 4D and 5B) was identified in an individual with marked skin alterations and severe brain abnormalities; these alterations influenced the alignment process and adversely affected the algorithm's choice of the largest slice for HC measurement, which included part of the ear, eye, and skin folds.

To consider a clinically meaningful difference, the value of the standard deviation of the HC measurement for the mean age of the participants (9.5 months, SD=1.3019 cm, [18]) was used to calculate the number of under and over estimated cases (Table 2). It can be observed that 75% and 76.6% of the cases measured by the algorithm would not have a systematic difference in relation to RAD_1 and RAD_2, respectively, in the clinical context.

Fig. 5 shows the representative cases with good and poor estimates of the algorithm utilization. For each case, we compared the HC_{mean} obtained by the algorithm and the mean of the HC measured by the two neuroradiologists (RAD_{mean}). Notably, we report an interesting case of a mismatch between the algorithm and RAD_{mean} (Fig. 5E), in which the individual was classified below two standard deviations (< 2.44 SD, microcephaly) by our method, but had been incorrectly identified qualitatively as showing severe macrocephaly by the radiologists, who were probably misled by the severe ventriculomegaly.

Head alignment was rated as excellent by both neuroradiologists, who considered it to be adequate and less time-consuming. Our algorithm also preserved the original image dimensions and voxel spacing in the aligned NIfTI file generated. In a Dell Inspiron 5480, Intel® Core™ i7-8565U CPU @ 1.80GHz 1.99 GHz, DDR4 memory RAM 16 GB, the mean execution time was 0.5685 s/slice (1.759 slices/s), around 105.54 slices/min.

In addition, in a third analysis of variance, we included a measurement of head circumference obtained through tape measurements to the HC_{mean}, RAD_1 and RAD_2 data. This analysis used the secondary database defined in Sec. 2.3.3. There was also a significant difference between HC_{mean}, RAD_1, RAD_2 and tape measurements ($F(3, 39) = 1.3182$, $p < 0.001$) evidenced by the ANOVA and post-hoc pairwise t-test. However, these measures were highly concordant (ICC[2, *k*] = 0.99) and consistent (ICC[3, *k*] = 1). The paired-sample t-test showed a significant difference between tape

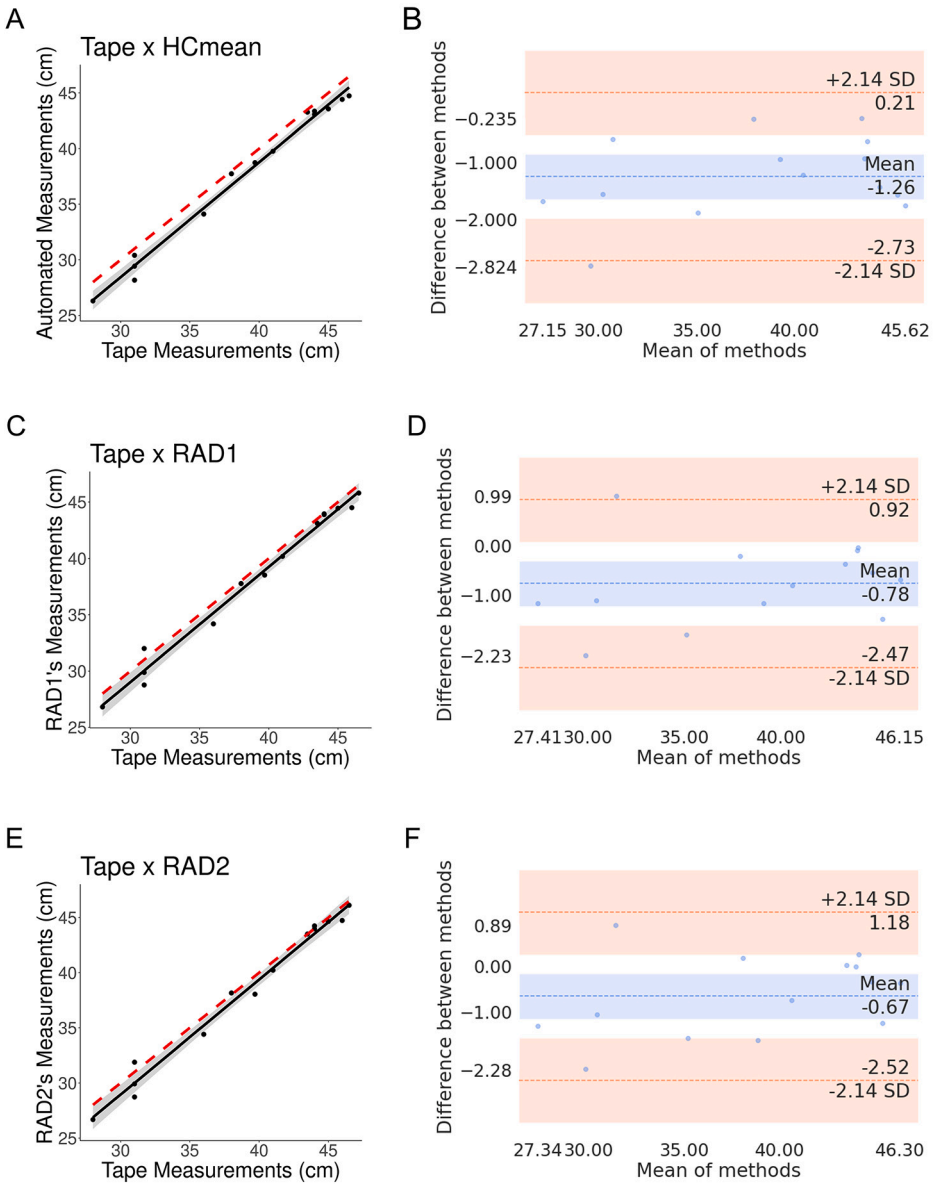

Fig. 6. (A) Dispersion plot for tape measurements vs. HC_{mean}. (B) Bland-Altman plot for tape measurements vs. HC_{mean}. (C) Dispersion plot for tape measurements vs. RAD_1. (D) Bland-Altman plot for tape measurements vs. RAD_1. (E) Dispersion plot for tape measurements vs. RAD_2. (F) Bland-Altman plot for tape measurements vs. RAD_2. Bland-Altman plots use 95% confidence intervals for the mean difference according to Student's t Table. RAD_1 and RAD_2 denote the HC measured by neuroradiologists and HC_{mean} is the average of three serial automated HC measures. The red dashed line on (A), (C) and (E) represents the maximum correlation.

measurements (38.91 ± 6.44 cm) and the other raters: HC_{mean} (37.65 ± 6.69 cm; $t(13) = -6.613$, $p < 0.001$), RAD_1 (38.13 ± 6.64 cm; $t(13) = 3.540$, $p = 0.004$) and RAD_2 (38.24 ± 6.76 cm; $t(13) = -2.812$, $p = 0.015$), although the high correlation between each rater (rho = 0.988, 0.994, 0.990, respectively) – see Fig. 3C. Fig. 6 shows the dispersion (6A, C, E) and Bland-Altman (6B, D, F) plots for tape measurements vs HC_{mean}, RAD_1 and RAD_2, respectively.

Our proposed method tends to underestimate HC in comparison with the head tape. The mean absolute error was 1.259 cm between the HC_{mean} and head-tape measurements, which can be clinically meaningful. We observe that this difference has the typical magnitude of a standard deviation for the HC of the sample mean age [18], which may underscore the patient's classification, as shown in Table 2. We observe that this underestimation also occurs between the HC measured by RAD_1 and RAD_2 in comparison with the head tape (MAE = 0.918 cm, 0.859 cm, respectively). This underestimation is possibly related to the fact that the alignment and slice selection likely occur in planes different from those measured by the head tape. In addition, the head CT image acquisition plan depends on the CT gantry angulation, which is selected in a standardized plane (e.g., the orbitomeatal line), using lateral scan projection radiography as a reference [31]. Thus, the CT image acquisition plan was not programmed to match measurements obtained by the head tape. Moreover, head-tape measurements were compared to HCs obtained from CT scans with considerably thicker slices (i.e., lower number of images – see Supp. Table 2 for scanner settings) relative to the scans from the primary dataset. In addition, clinical measurements were not acquired on the same day of the CT examination (2.07 ± 1.62 days).

4. Discussion

Our algorithm for obtaining automated HC measurements showed high concordance and consistency across three consecutive evaluations. Moreover, compared to manual HC measurements obtained by two neuroradiologists and measurements using a measuring tape, the automated quantifications also showed high

agreement and correlation. Thus, the findings indicate the potential clinical value of the proposed HC measurement and suggest that it can be an automated and accurate CT-based method for macrocephaly and microcephaly screening and follow-up, when the patient's CT image is already available.

In addition to manual HC measurements, other studies have explored the use magnetic resonance imaging (MRI; [32]), and CT imaging [24]. Automated methods using MRI to measure head circumference may bypass the provider-dependent challenges brought forth by manual measurements and ultrasound techniques [32]. However, MRIs are cost prohibitive and access is limited in developing countries like Brazil, impeding any large-scale implementation of automated MRI HC measurements [14].

A small-scale study by [24] previously investigated the performance of an automated algorithm to measure skull circumference in pediatric populations using CT. Their method, however, requires both inputs other than the CT scan itself and the use of proprietary software. These limitations prevented us from evaluating their algorithm's performance on our dataset. Our proposed algorithm only uses open-source software and is fully automated.

This study comes with some limitations. First, our sample consisted of 35 individuals with microcephaly (31 in the primary dataset and 4 in the secondary dataset) and nine with macrocephaly (all in the primary dataset). A larger number of pathological cases with abnormal HCs would be ideal for assessing performance, but CT datasets with this profile were limited, as shown by [3] and [12]. While we have tested our method using real-world data from different clinical centers, we need a larger, more representative sample to determine the effect that varying acquisition scanner parameters and study locations have on the solution's performance. In addition, the effect of different Z-axes on HC measurements might be acceptable because head-shape modifiers do not occur abruptly within the slices [32]. Moreover, because registration is performed for automated head alignment, our algorithm may underperform when images show substantial skull deformities or brain alterations.

Head circumference can be simply and cheaply measured using a measuring tape whereas CT scanning as a procedure is expensive and carries a real risk to the infant – both because of the need for sedation for the procedure and the long term cancer risk due to the radiation exposure. Thus one could not ethically opt to use CT scanning instead of direct measurement. Therefore, we emphasize that this model is not intended to replace manual HC measurement, and we use CT images already saved in the hospital database.

Wright and Emond [29] indicated that head circumference has weak predictive power, having low sensitivity and specificity for important conditions. Despite this, its strong point is its low cost and simplicity as an initial screening measure and it is still a protocol established by the WHO. Although other measurements, such as brain volume, may be more useful [17] for clinical assessment, the HC measurement is widely used and disseminated in clinical routine with professionals trained in their use and interpretation.

Studies have observed that the WHO standard is not suitable for different ethnicities, with discrepancies and bias in diagnoses of macrocephaly and microcephaly in European and Asian populations. In this sense, using local population-specific thresholds or references are more appropriate for many populations [9,30,10]. Retrospectively, the proposed method can be a single-protocol alternative for creating growth reference tables for HC, for regions where currently available tables are not suitable due to ethnic differences or even for syndromes with head circumference alterations [28].

The WHO Child Growth Standards table provides reference values for children up to five years of age. A normative growth chart up to the age of 18 years was presented by Woods and Parker [28], and preterm charts [26,27] for assessments of premature newborns are also available. Our method can be used for measurements in individuals of any age, if the head CT scan is already available.

We developed an algorithm for automated measurement of head circumference, using CT scans, which we hope will facilitate the assessment of neurodevelopmental disorders associated with abnormalities in head circumference.

CRediT authorship contribution statement

Priscila Satomi Acamine: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Rafael Maffei Loureiro:** Data curation, Methodology, Validation, Writing – review & editing. **Lucas dos Anjos Longas:** Data curation, Software, Validation, Writing – review & editing. **Fabio Augusto Ribeiro Dalpra:** Data curation, Methodology, Validation, Writing – review & editing. **Luigi Villanova Machado de Barros Lago:** Formal analysis, Software, Writing – review & editing. **Larissa Vasconcellos de Moraes:** Data curation, Software, Validation, Writing – review & editing. **Paulo Cesar Filho Estevam:** Software, Validation, Writing – review & editing. **Luiz Otávio Vittorelli:** Data curation, Writing – original draft, Writing – review & editing. **Lucas Silva Kallás:** Writing – review & editing. **Ana Paula Antunes Pascalicchio Bertozzi:** Data curation. **Maria Isabel Barros Guinle:** Writing – review & editing. **Gilberto Szarf:** Writing – review & editing. **Saulo Duarte Passos:** Data curation, Methodology, Writing – review & editing. **Birajara Soares Machado:** Conceptualization, Funding acquisition, Project administration, Writing – review & editing. **Joselisa Péres Queiroz De Paiva:** Conceptualization, Supervision, Writing – original draft.

Ethics statement

The authors state that they have obtained appropriate institutional review board approval or have followed the principles outlined in the Declaration of Helsinki for all human or animal experimental investigations.

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Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.neuri.2025.100217.

Data availability

The data that support the findings of this study were provided by Hospital Roberto Santos (MBPS and DNS) and Hospital Universitário da Faculdade de Medicina de Jundiaí (SDP) and are not publicly available to preserve confidentiality of research participants. The source code is an intellectual property of the Brazilian Ministry of Health and can be available from the corresponding author upon reasonable request.

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