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Original Article

Three-dimensional breast imaging using Artificial-Intelligence-Based Automatic Measurement System

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ABSTRACT

Background: Three-dimensional (3D) image technology in breast measurement requires exploration. We aimed to evaluate a new automatic breast measurement system based on artificial intelligence (AI).

Methods: This prospective controlled study included all-women patients who underwent breast reconstruction from January to May 2022. Patients underwent 3D scanning before breast reconstruction. Two doctors performed the measurements twice through AI and manual measurements on the 3D images, respectively. The measurement results of bilateral breast width, convexity, height, volume, and measurement time were recorded. Consistency analyses were performed.

Results: Fifty-eight patients (116 breasts) were recruited. For the left breasts, AI and manual measurements showed excellent con-

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sistency (intra-class correlation coefficients (ICC) = 0.81) in width measurements, moderate consistency (ICC = 0.59) in height measurements, excellent consistency (ICC = 0.87) in convexity measurements, and good consistency (ICC = 0.74) in volume measurements. For the right breasts, the width consistency was excellent (ICC = 0.93), height consistency was good (ICC = 0.65), convexity consistency was excellent (ICC = 0.94), and volume consistency was excellent (ICC = 0.85). The Bland–Altman curves also showed that the measurement results were comparable and few outliers were detected. AI average measurement time (compared to manual measurements) was significantly shorter (40.65 ± 1.51 s vs. 610.47 ± 18.74 s; $p < 0.001$).

Conclusion: The AI-based 3D breast measurement system showed high accuracy, better reproducibility, and significantly shortened the measurement time, which could help guide surgical management.

Introduction

Breast reconstruction surgery has currently become an important part of breast cancer surgery. Accurate breast measurement is an important for formulating a perfect preoperative plan, intraoperative decision-making, and postoperative aesthetic effect assessments. Although there have been various methods for measuring breasts (such as mammography, magnetic resonance imaging (MRI), and computed tomography), the most widely accepted approach involves using anthropometric measurement methods.[1]

Three-dimensional (3D) imaging technology is a mature technology that is widely used in industries to analysis objects and their shapes. Compared with the traditional anthropometric methods, 3D imaging can objectively represent measurement results by providing real surface anatomical shapes, and it can provide more 3D information, such as surface area and volume.[2] Several studies have confirmed the use of 3D imaging in the clinical context of breast surgery.[1-4] Currently, commercial 3D devices and software are generally expensive and complex to operate.[5] Studies have shown that breast volume is often underestimated in women with larger breasts because it is difficult to consistently identify breast boundaries.[6] These characteristics limit this technology's use in daily practice.

In recent years, artificial intelligence (AI) has been driven by advancements in processing power, memory, storage, and large amounts of data, leading to remarkable achievements in medical imaging, pathological imaging, disease prognosis prediction, and other fields.[7-9] In image processing, AI technology can greatly improve the working speed, reduce the processing cost, and improve the accuracy of image recognition. In this study, we developed a system for measuring 3D breast models, based on a deep convolutional neural network, which provides clinical data and helps guide surgical management. Using this system, surgeons can quickly and intuitively evaluate the size, shape, and contour of the breast, to obtain quantitative breast measurements and volume calculations. The purpose of this study was to verify the accuracy and assess the reliability of our AI measurement system for 3D breast imaging to measure breast dimensions in 3D images.

Patients and methods

We designed a prospective experiment, which was conducted by following the Declaration of Helsinki and approved by the local medical ethics committee and registered under number bc2023176.

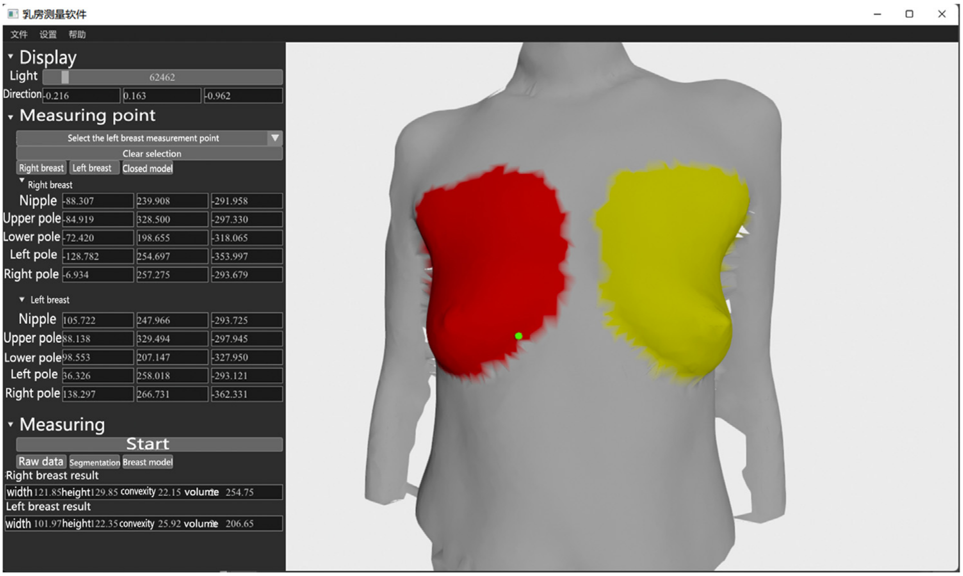

Figure 1. Result of 3D breast imaging using AI-based automatic measurement system.

This study included women who received breast reconstruction surgery at the Tianjin Medical University and Cancer Hospital (China, Tianjin) from January to May 2022. The 3D scans were performed before breast reconstruction surgery. All image files were processed using 3D engineering software and our self-developed 3D breast AI measurement system "Tianzhong 3D Breast Automatic Measurement System" (Figure 1). This system was co-developed by our team and Nankai University (China, Tianjin) and it has registered for the Copyright of Computer Software in China (14223135). Patients with a history of breast surgery and those with breast weights or volumes <100 g/mL or >1000 g/mL were excluded.

Our self-developed 3D AI breast measurement system consists of a handheld 3D scanning instrument, a personal computer, and our own AI breast measurement software. We used an EinScan Pro 2X structural sensor 3D scanner (SHINING 3D Inc., China) for scanning, and it was connected to a PC laptop. We analyzed the 3D breast data, which were manually measured and calibrated through machine learning, and developed the AI breast measurement software.

At present, there are software packages that can measure 3D engineering images. By reviewing the literature, we found that >25% of the current research on 3D breast data measurement has used Geomagic Studio, and all these studies showed good accuracy and repeatability.[10] Therefore, in this study, we chose the measurement results of Geomagic Studio as the standard parameter to compare with our AI measurement system.

All the systems used worked in rooms with normal lighting, and experienced surgeons performed the 3D scanning on the patients undergoing breast reconstruction for breast cancer. All scanned files were imported into the Geomagic system and our self-developed AI measurement system, and 2 readers measured the 3D images twice and obtained the following clinical measurements for each breast: width, height, convexity, volume of bilateral breasts, and time for measurement. As Geomatic Studio cannot directly measure the convexity in manual measurements, we manually marked 3 points (one point in the middle of the lower breast boundary, one in the upper breast boundary, and one in the lateral breast boundary) to build a horizontal plane to simulate the chest wall, and then we measured the vertical distance from the nipple to this horizontal plane as the breast convexity. In our self-developed software, all parameters, including convexity, were automatically measured through algorithms.

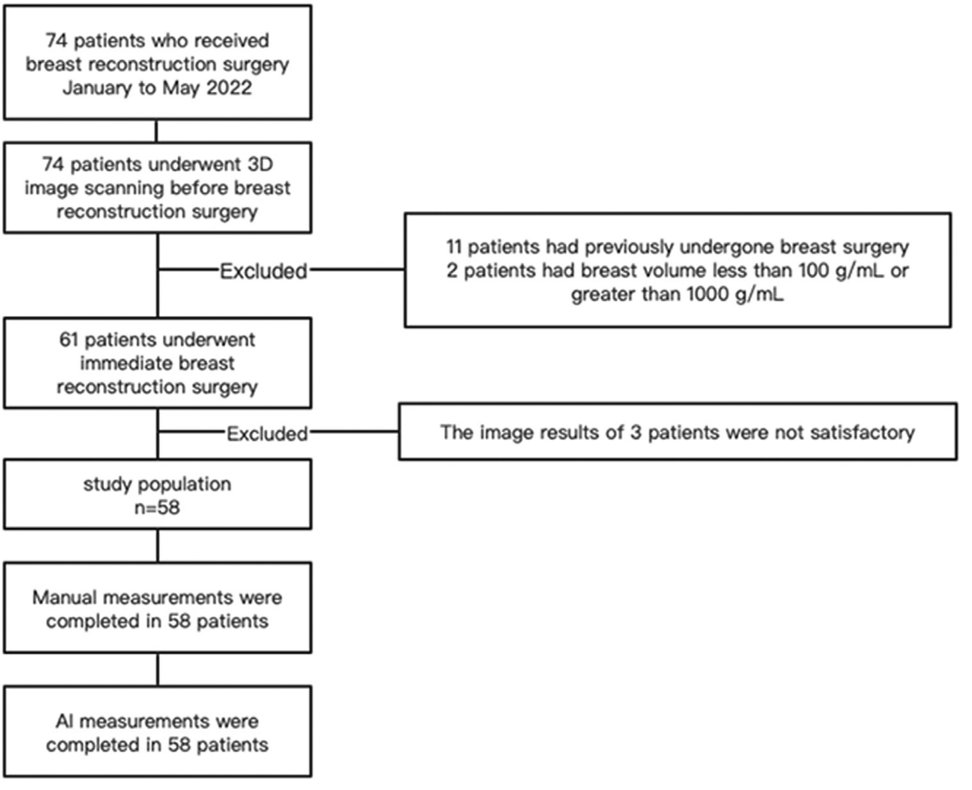

Figure 2. Flow diagram of the study selection and inclusion process.

All measurements were continuous variables and expressed as means ± standard deviations (SDs). The Kolmogorov–Smirnov test was used to assess whether the measured values were normally distributed. A paired t-test was used to identify significant differences between the results from the readers and AI methods. We used manual measurement data as references. For continuous variables, the consistency between Geomagic Studio and the system developed by us, as well as the consistency between the 2 readers (doctors), was evaluated using intra-class correlation coefficients (ICCs) and Bland–Altman analyses. The level of the protocol was divided into the following categories: poor (ICC = 0–0.20), fair (ICC = 0.21–0.40), moderate (ICC = 0.41–0.60), good (ICC = 0.61–0.80), and excellent (ICC = 0.81–1.00). All statistical analyses used SPSS software version 19.0 and Prism 9.0. Statistical significance was defined as $p < 0.05$.

Results

The study was conducted in our hospital (Tianjin Medical University & Cancer Hospital) from January to May 2022. A total of 74 patients underwent 3D image scanning before breast reconstruction surgery. Among them, 16 patients with histories of previous breast surgeries, patients with breast weights or volumes of <100 g/mL or >1000 g/mL, and patients with unsatisfactory 3D image effects were excluded. After considering the inclusion and exclusion criteria, a total of 58 patients (116 breasts) participated in the study (Figure 2). No statistical differences were found for all distances measured manually and using AI for the 3D images ($p > 0.05$).

The results of AI measurement and manual measurement are shown in Table 1. In detail, the following results were observed in the AI measurements of the breast parameters: the average widths

Table 1
Results from the AI and manual measurements.

	(cm)	AI measurements (Reader 1 vs. Reader 2)				Manual measurements (Reader 1 vs. Reader 2)			
		Reader1 ± SD	*Reader2 ± SD*	*Mean ± SD*	*SE*	*Reader1 ± SD*	*Reader2 ± SD*	*Mean ± SD*	*SE*
LEFT BREAST	Width	13.76 ± 1.3	13.96 ± 1.25	13.86 ± 1.24	0.16	14.91 ± 1.74	15.05 ± 1.63	14.98 ± 1.65	0.22
	Height	12.7 ± 1.96	12.55 ± 1.76	12.63 ± 1.75	0.23	13.59 ± 1.64	13.53 ± 1.64	13.56 ± 1.53	0.20
	Convexity	4.08 ± 1.07	4.12 ± 1.24	4.10 ± 1.11	0.15	4.63 ± 1.64	4.75 ± 1.21	4.69 ± 1.15	0.15
	Volume	455.8 ± 148.0	451.1 ± 155.2	453.5 ± 148.4	19.48	562.8 ± 261.4	573.4 ± 306.9	568.2 ± 275.4	36.17
RIGHT BREAST	Width	14.42 ± 1.55	14.51 ± 1.36	14.47 ± 1.41	0.19	15.06 ± 1.66	15.06 ± 1.69	15.06 ± 1.65	0.22
	Height	12.79 ± 1.89	12.65 ± 1.87	12.72 ± 1.77	0.23	13.5 ± 1.54	13.06 ± 1.59	13.29 ± 1.43	0.19
	Convexity	4.30 ± 1.11	4.32 ± 1.14	4.31 ± 1.10	0.14	4.58 ± 1.2	4.57 ± 1.17	4.58 ± 1.15	0.15
	Volume	500.2 ± 163.4	492.0 ± 171.4	496.1 ± 164.9	21.65	561.1 ± 293.9	548.3 ± 245.9	554.7 ± 265.0	34.8

AI, artificial intelligence. SD, standard deviation. SE, standard error.

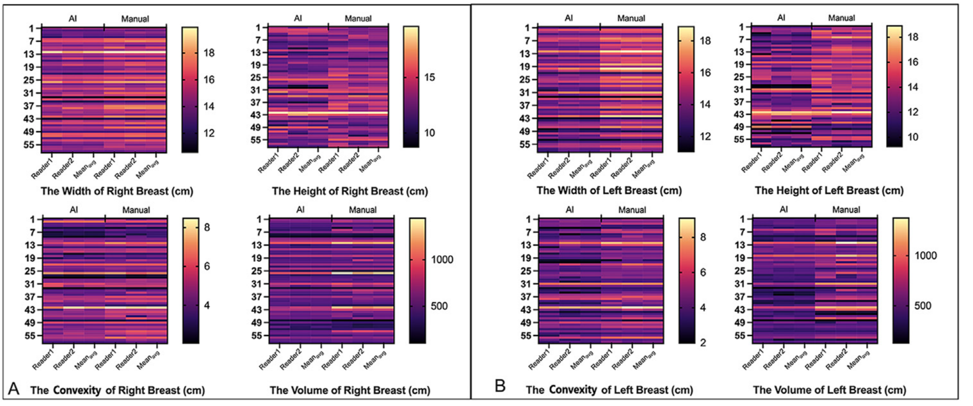

Figure 3. Heat maps of bilateral breast measurement results. (A) Heat maps of right-breast measurement results. (B) Heat maps of left-breast measurement results.

of the left breasts measured using AI and manually were 13.86 cm (SD = 1.24 cm) and 14.98 cm (SD = 1.65 cm), respectively; the average AI and manual right-breast width measurements were 14.47 cm (SD = 1.41 cm) and 15.06 cm (SD = 1.65 cm), respectively; the average left-breast height AI and manual measurements were 12.63 cm (SD = 1.75 cm) and 13.56 cm (SD = 1.53 cm), and those for right-breast height were 12.72 cm (SD = 1.77 cm) and 13.29 cm (SD = 1.43 cm), respectively; the average convexity distances of the left breasts measured using AI and manual measurements were 4.10 cm (SD = 1.11 cm) and 4.69 cm (SD = 1.15 cm), respectively, and those for right breasts were 4.31 cm (SD = 1.10 cm) and 4.58 cm (SD = 1.15 cm), respectively; and, finally, the average left-breast volume was 453.45 cm^3 (SD = 148.36 cm^3) by AI measurements and 568.17 cm^3 (SD = 275.44 cm^3) by manual measurements, and those for right-breast volume were 496.09 cm^3 (SD = 164.86 cm^3) and 554.72 cm^3 (SD = 264.99 cm^3), respectively. There was a significant difference between the 2 groups ($p < 0.001$) (Figure 3).

The average time measured using AI for Reader 1 was 39.58 ± 1.53 s, and for Reader 2, it was 41.63 ± 1.49 s, while the average time for the AI measurements was 40.65 ± 1.51 s. The time required for the manual measurements was 596.53 ± 17.65 s for Reader 1 and 624.41 ± 19.23 s for Reader 2. The average time for the manual measurements was 610.47 ± 18.74 s (Figure 4). There was a significant difference between the 2 groups ($p < 0.001$).

Among the results of the ICC consistency analysis for the AI measurements (Table 2), 2 readers had excellent consistency in their measurements of the left and right-breast widths (ICC = 0.89 and 0.88, respectively), height measurements had good consistency (ICC = 0.76 and 0.77, respectively), and convexity measurements had excellent consistency (ICC = 0.85 and 0.90, respectively). The volume measurement consistency was also excellent (ICC = 0.92 and 0.94, respectively). The manually measured widths had excellent consistency (ICC = 0.92 and 0.94, respectively), height measurements had good consistency (ICC = 0.73 and 0.64, respectively), convexity measurements had excellent consistency (ICC = 0.89 and 0.86, respectively), and volume measurements had excellent consistency (ICC = 0.88 and 0.91, respectively). The Bland–Altman curves of the AI and manual measurement results showed that the measurement results were comparable and few outliers were detected (Figure 5).

In the consistency analysis results that compared the AI and manual measurements for the left breasts (Table 3), the widths showed excellent consistency (ICC = 0.81), heights showed moderate consistency (ICC = 0.59), convexity showed excellent consistency (ICC = 0.87), and volume consistency was good (ICC = 0.74). The results of the ICC comparisons for right breasts also indicated the reliability of the AI measurement as the widths had excellent consistency (ICC = 0.93), heights had good consistency (ICC = 0.65), convexities had excellent consistency (ICC = 0.94), and volumes had excellent consistency (ICC = 0.85).

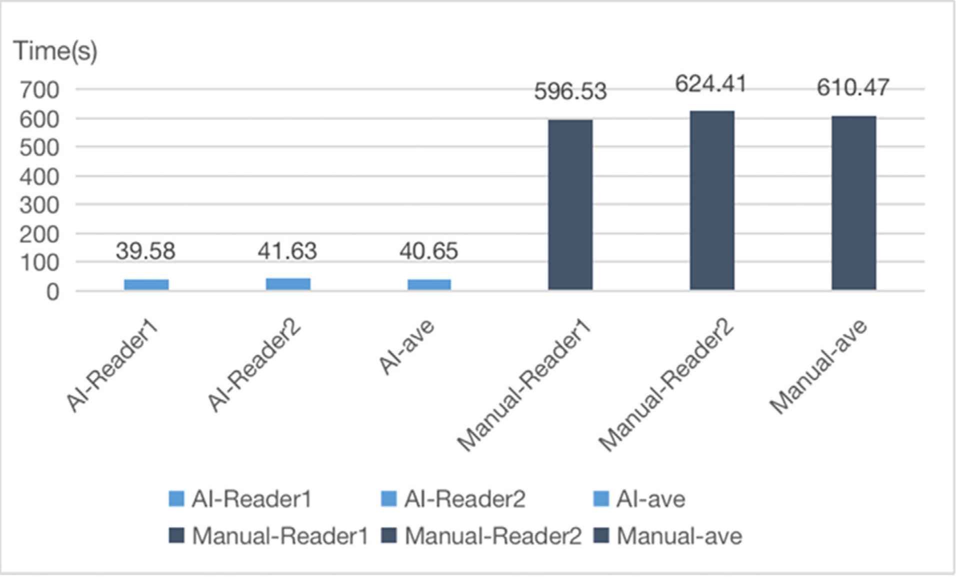

Figure 4. Time measurement comparisons between AI and manual measurements. AI, artificial intelligence.

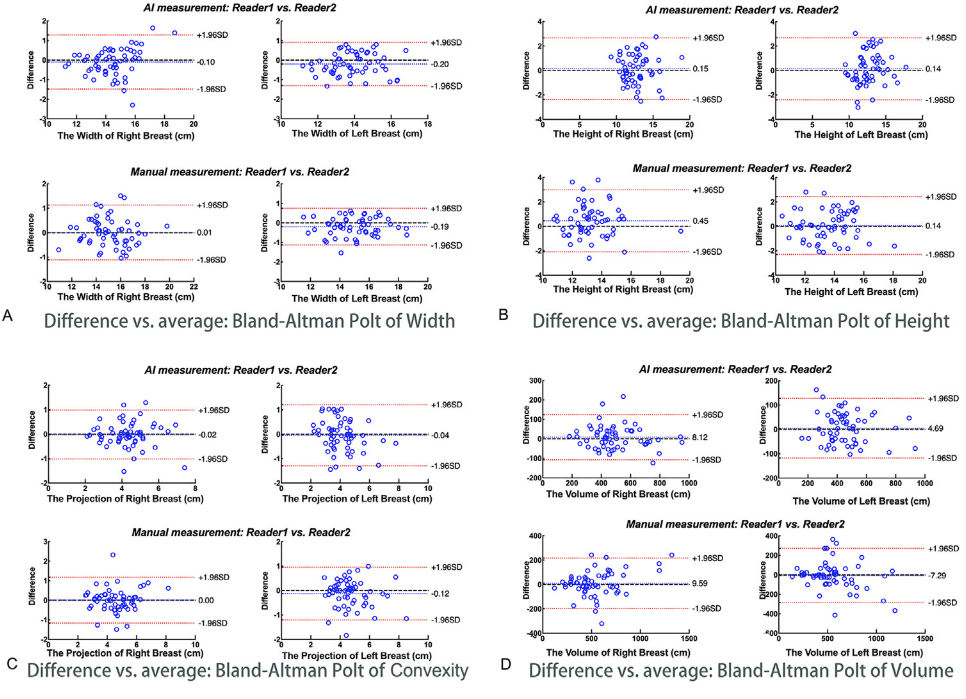

Figure 5. Bland–Altman curves for the AI and manual measurement results. (A) The Bland–Altman plots for breast widths. (B) The Bland–Altman plots for breast heights. (C) The Bland–Altman plots for breast convexities. (D) The Bland–Altman plots for breast volumes. AI, artificial intelligence.

Table 2
Consistency analysis results for the measurements recorded by Reader 1 and Reader 2.

		AI measurements (Reader 1 vs. Reader 2)					Manual measurements (Reader 1 vs. Reader 2)					
		Absolute agreement		Bland–Altman			Absolute agreement		Bland–Altman			
		ICC	95% CI	Bias	95% LOA	SD	ICC	95% CI	Bias	95% LOA	SD	p
LEFT	Width	0.89	0.81,0.94	-0.20	-1.31,0.91	0.56	0.92	0.86,0.95	-0.19	-1.13,-0.74	0.48	p<0.001
BREAST	Height	0.76	0.62,0.85	0.14	-2.4,2.69	1.30	0.73	0.58,0.83	0.06	-2.31,2.43	1.21	p<0.001
	Convexity	0.85	0.76,0.91	-0.04	-1.3,1.21	0.64	0.89	0.82,0.93	-0.12	-1.20,0.96	0.55	p<0.001
	Volume	0.92	0.86,0.95	4.69	-118,127.4	62.60	0.88	0.80,0.92	-7.29	-285.00,270.50	141.70	p<0.001
RIGHT	Width	0.88	0.81,0.93	-0.10	-1.48,1.29	0.71	0.94	0.91,0.97	0.01	-1.11,1.13	0.57	p<0.001
BREAST	Height	0.77	0.64,0.86	1.20	-2.70,2.70	1.29	0.64	0.45,0.77	0.45	-2.08,2.98	1.29	p<0.001
	Convexity	0.90	0.84,0.94	-0.02	-1.02,0.98	0.91	0.86	0.80,0.92	0.00	-1.16,1.17	0.60	p<0.001
	Volume	0.94	0.90,0.97	8.12	107.5,123.8	59.00	0.91	0.86,0.95	9.59	-197.10,216.30	105.50	p<0.001

AI, artificial intelligence. ICC, intra-class correlation coefficient. CI, confidence interval. LOA, limits of agreement. SD, standard deviation.

Table 3
Consistency analysis results of the AI and manual measurements.

		Absolute agreement		Bland–Altman			
		ICC	95% CI	Bias	95% LOA	SD	p
LEFT BREAST	Width	0.81	0.15,0.94	-1.09	-2.45,0.27	0.7	p<0.001
	Height	0.59	0.25,0.77	-0.94	-4.21,2.34	1.67	p<0.001
	Convexity	0.87	0.29,0.96	-0.59	-1.69,0.51	0.56	p<0.001
	Volume	0.74	0.42,0.87	-102.7	-363.6,158.3	133.1	p<0.001
RIGHT BREAST	Width	0.93	0.51,0.98	-0.59	-1.7,0.52	0.57	p<0.001
	Height	0.65	0.41,0.80	-0.55	-3.68,2.57	1.59	p<0.001
	Convexity	0.94	0.86,0.97	-0.26	-1.17,0.65	0.46	p<0.001
	Volume	0.85	0.73,0.91	-50.15	-269.30,169.00	111.80	p<0.001

AI, artificial intelligence. ICC, intra-class correlation coefficient. CI, confidence interval. LOA, limits of agreement. SD, standard deviation.

Discussion

The breast is irregular and soft, with a hemispherical shape. Accurate preoperative measurements of the breasts are essential for ensuring good symmetry and satisfaction after breast reconstruction.[11] At present, the methods that are typically used for breast measurements include anatomic (anthropometric), thermoplastic casting, the Archimedes procedure (immersion in water), the Grossman–Roudner device, and imaging methods (computer tomography (CT)/ MRI).[12] The application of 3D imaging in breast surgery is rapidly developing, and several studies have verified the accuracy and repeatability of this technology compared to the traditional methods.[10,11,13]

Today, anthropometry is the most widely used method worldwide. However, breast volume cannot be measured using traditional anthropometry. In clinical practice, in several cases, the volume of breast tissue is directly measured using the Archimedes' procedure.[13] Previous studies have confirmed that there is a good correlation between the 3D technology used to evaluate breast volume and volume measured using the Archimedes procedure. In addition, comparisons between breast volume measurements obtained using 3D scanning technology and reference measurements based on CT/MRI data also show a high degree of consistency and significant correlation.[11,14,15] However, because patients are in a prone position during CT/MRI measurements, the 3D scanning results of patients in a standing position are closer to the actual breast parameters.[16]

We believe that 3D scanning has great potential for the future of breast surgery. However, practical applications with 3D software and hardware are limited by their high prices and complicated operations.[4] In previous similar studies, the equipment costs for handheld 3D scanners ranged from approximately USD 379 to USD 19,000.[10] Three-dimensional scanning equipment includes handheld and fixed scanners.[13] We considered that the expenditures related to handheld 3D scanners have the advantages of portability and low cost compared with fixed scanners.[17] After connecting to a computer, the equipment can be used in outpatient clinics, wards, and operating rooms. The price of the handheld equipment used in our study was approximately USD 7500. Some studies have shown that there are no differences in the measurement results between a USD 379 equipment and an equipment valued at >USD 10,000.[4] However, the minimum resolution standard for 3D breast-scanning images or equipment is not clear.

The process of 3D breast-scanning is fast, lastly approximately 30–50 s. Compared with CT/MRI, 3D scanning can dramatically reduce the scanning time, saving costs and manpower.[18] Although the scanning process for 3D imaging is very convenient, the measurement process for 3D image parameters continues to be cumbersome. At present, 3D engineering measurement software is typically used in research on 3D breast image measurements, and it does not usually fully meet the requirements of breast measurement. The software post-processing time for 3D scanning is less than the time required for CT imaging (90 min) and MRI imaging (13–30 min), but it may still take longer. Although this kind of software can provide powerful functions, it is complex in operation and learning, and the software cost is high.[4,19] 3D image scanning and processing software is often sold with scanners. Moreover, such software are very expensive when purchased alone as the price range is approximately USD 9500–20,000.

AI has become an integral approach in resolving numerous complex operations or tasks with high accuracy. In recent years, the application of AI in the medical field has become a hot research topic.[1] Recently, Akhoondinasab et al. published the results of a study on measuring breast volume using AI.[20] They first manually measured various parameters of the breasts and then predicted breast volumes based on the results of the manually measured parameters through AI. Our AI measurement system simplifies the measurement process. It can directly analyze and segment the 3D breast images and obtain the vector parameters and volumes of the breasts simultaneously. Compared with manual measurements, our AI system can greatly reduce the time required for 3D breast image measurement to 1/15th of the time required by conventional methods.

The accuracy of 3D image measurements in 3D engineering software is related to the level of personal experience.[21,22] Generally, the more proficient a doctor is, the more accurate the result will be. AI measurements can avoid measurement deviations caused by personal experience. Training the model using a large number of data samples can improve the accuracy of machine-learning medical image segmentation. In the first training and learning stage, we used the manually calibrated data of 500 female breasts for analysis, which ensured the accuracy and stability of the AI measurements.

Although it was observed that the measurements made using AI and experienced doctors contained minor errors in some parameters, there was no statistically significant difference in our study. Generally, the results proved the possible application of AI for breast measurements. The consistency between the AI and manual measurements was satisfactory, but we found that the AI measurement results were generally slightly lower than the manual measurement results. This may have been due to the insufficient number of data sets for the machine training and learning. This shows that we need to continue machine learning to improve its stability and accuracy in the future.

When a patient is standing, due to the breast being in a lolling state, the upper boundary of the breast usually lacks clear anatomical characteristics. Some studies have used surface curvature analysis to calculate the breast boundary,[23] but such a system was developed for using 3D measurements to direct the assessment of breast ptosis and it cannot predict breast volume. Owing to slight differences in subjective reasons, 2 calibrations of the upper boundary of the same breast are practically impossible to superimpose accurately.[24] This will affect the accuracy and repeatability of breast height parameter measurements. We were surprised to find that the measurement consistency of the AI breast height measurement results of the 3D images was higher than that of the manual measurements. This means that the AI could better define the upper boundaries of the breasts and obtain more stable results.

Although the current research has shown that a 3D scanning system can be used as a powerful tool for breast measurements to provide objective data for surgeons, there are still some limitations that hinder effective breast measurements under any conditions. Because 3D scanning involves surface scanning, it cannot penetrate the breast tissue. Sometimes, a breast is too large or too droopy and 3D scanning cannot obtain an image of the interspace between the chest and posterior border of the breast/dorsal limit of the breast.[18] When there is a small missing area in the 3D images, we can use professional 3D engineering software to patch the image and fill in the missing part. However, if there are several missing images, they cannot be repaired smoothly.

The main purpose of this study was to evaluate the ability of AI in measuring 3D breast images. This article is an initial result of our research. According to our experimental results, in 3D breast images, the AI measurement ability is close to the manual measurement and can save a considerable amount of time. With continuous learning, the accuracy of AI can be further improved in the future. We hope that this program can replace traditional human surface measurement methods in the future and assist doctors in developing preoperative surgical plans. There are still several potential research directions in 3D breast imaging. Except for using Breast-Q questionnaire and photographs, 3D breast images can also be used for aesthetic evaluation after breast reconstruction surgery.[25] In addition, the combination of 3D breast imaging with 3D printing or virtual reality (AR/VR) may further improve perioperative efficiency.[26,27] We believe that this is a very promising research direction.

Conclusions

Accurate parameter and volume measurements are an integral part of preoperative planning in breast reconstructive surgery. Although 3D scanning can provide accurate and detailed results, the disadvantages of difficulty in operating and having a long image processing time are evident. 3D scanning had limited practicability before the introduction of AI measurements. We tried to ensure the accuracy and improve the efficiency of the method using a new algorithm for machine learning. Our study verified the accuracy and reproducibility of the AI technology in measuring breast parameters and volumes. In particular, it greatly shortened the measurement time in 3D breast images. This shows that an AI measurement system can bring good economic benefits. In conclusion, this study validated the use of AI for breast surface measurements. However, further research in this area is needed to develop standardized procedures that can be used in reconstructive surgery practices.

Conflicts of interest statement

None.

Ethical approval

This study was approved by the local medical ethics committee and registered under number bc2023176.

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None.

Author contributions

Conceptualization, Shu Wang, Lei Ren, and Jihua Liu; methodology, Shu Wang, Lei Ren, and Bo Ren; software, Bo Ren; validation, Shu Wang; formal analysis, Shu Wang, Lei Ren, and Jihua Liu; investigation, Shu Wang, Lei Ren and Jihua Liu, Shanshan He, and Cong Su; resources, Jian Yin and Bo Ren; data curation, Shu Wang, Shanshan He, and Cong Su; writing—original draft preparation, Shu Wang, Lei Ren, and Jihua Liu; writing—review and editing, Jian Yin; visualization, Shu Wang, Lei Ren and Jihua Liu; supervision, Jian Yin; project administration, Jian Yin and Bo Ren; funding acquisition, Jian Yin and Shu Wang. All authors have read and agreed to the published version of the manuscript.

Patient consent statement

Informed consent was obtained prior to the interview.

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