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Automated Ultrasound Image Segmentation Using AI: A Step Toward Non-invasive Kidney Disease Monitoring

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Abstract

Non-invasive kidney evaluation through ultrasound imaging is quite common, but there is always a challenge in manual analysis of the kidney boundaries because of noise, brightness variation, and dependence on operators. The paper will examine a basic threshold-based segmentation algorithm to improve kidney boundaries in ultrasound images and their performance under different levels of image quality. Twenty-five kidney ultrasound images were pre-processed under the standardization and noise-reduction steps, and an automated boundary was further created through pixel-intensity thresholding. The standard of comparison was made of manual boundaries. The findings showed that the automated process had a close correspondence with manual contours in the majority of the cases, especially with the images that had moderate to high clarity. Comparison of the clarity groups revealed that there was a slight deviation of good quality images, moderate deviation in quality scanners, and higher variation amongst areas where noise or shadowing was evident. Morphological analysis also confirmed that the automated result did not cause significant changes in the general kidney anatomy, besides the fact that certain areas that had weak contrast had little differences. Also, the process of segmentation improved the visualization of structures by decreasing the effect of speckle interference and accentuating structure boundaries. On the whole, it can be concluded that an easy-to-use threshold-based segmentation method can offer a good and understandable kidney boundary extraction that can serve as a practical alternative to routine monitoring and clinical decision support, particularly in resource-limited environments.

Keywords: Kidney ultrasound, Automated segmentation, Threshold-based method, Renal boundary detection, Ultrasound image analysis, Non-invasive monitoring

Introduction

One of the most common non-invasive modalities used to determine the structure and functioning of the kidney is ultrasound imaging due to its ease of use, safety, and real-time imaging [1]. As a result of the burden of chronic kidney disease that keeps increasing globally, the need for effective and standardized imaging evaluation has become even more vital [2]. Nevertheless, the conventional method of interpreting sonographic images is typically met with dependencies among operators, an imprecise delineation of the boundaries, and sonographic imaging artifacts, e.g., speckle noise and acoustic shadowing [3]. These restrictions frequently result in alterations of the diagnostic interpretation, thus the need for new imaging

methods that are analytical and supportive has been justified [4].

Latest artificial intelligence technologies have transformed the medical imaging sector by providing accurate diagnosis, automated analysis, and reproducibility [5]. The use of AI in renal ultrasound has been growing at a fast pace, and its results have shown great enhancement in tissue characterization and accuracy of segmentation [6]. Segmentation models based on deep neural networks, specifically, have demonstrated a high potential to identify kidney boundaries with high precision when they are trained on trimmed and annotated datasets [7]. Other previous inventions, like dynamic graph-cut models, have also played a significant role in the better kidney boundary

extraction in 2D ultrasound [8]. Advanced networks using pixel classification and boundary regression have also enhanced the performance of segmentation of difficult imaging conditions [9].

Simultaneously, other refinement-based and multi-stage, and hybrid segmentation approaches have shown significant performance improvements even in various brightness and noise situations [10]. Some combination of multiple feature maps and better boundary-refinement strategies has also enhanced the accuracy of automated delineation [11]. Simultaneously, changing clinical understandings are placing stress on the variation in kidney structure across age and disease, and on the importance of segmentation techniques that can enable the morphological variability [12]. Basic pictorial and anatomic studies also outline the inherent difficulties of interpretation of renal ultrasound, such as a change in image quality and complicated anatomy [13]. The variations in these images suggest that improved boundary extraction is essential to aid in proper assessment [14].

Although there has been a significant improvement in AI-based imaging, the ultrasound segmentation remains impacted by inherent image constraints, including noise, shadowing, and irregularly changing echogenicity that complicate the manual and automated segmentation [15]. This thus makes the use of simple, computationally efficient segmentation strategies useful, especially where resources are limited. The paper at hand attempts to test a simple threshold-based segmentation algorithm to extract kidney boundaries in different qualities of ultrasound images and to ascertain whether this type of algorithm is acceptable as an aiding device in non-invasive monitoring of the kidneys.

The main aim of this research paper was to assess the performance of a basic threshold-based segmentation approach to obtain the kidney boundaries of ultrasound images. Particularly, it was expected to evaluate the accuracy of segmentation at different levels of image clarity, to test the consistency of the technique in the presence of various noise levels, and to compare the performance of automated boundaries to the performance of manually defined references to evaluate morphological consistency. Another aim was to investigate the possibility of improving the quality of visualization and non-invasive kidney tracking with the help of this lightweight segmentation method in a standard clinical environment.

Methods

Study Design

It was a descriptive analytical study based on a set of kidney ultrasound images collected on clinical repositories and publicly available imaging datasets. The photos in the research were chosen according to specific quality standards, such as sufficient brightness, a clear image of renal organs, proper labelling of anatomy, and general clinical usefulness to evaluate the kidney. The images that only contained a high amount of resolution and had a small number of artifacts were left to be further processed.

Data Preparation

The conversion of all selected images to a similar format was done to be consistent in the further analysis. Simple post-processing measures were used to increase the quality of images and the visibility of renal borders. The measures mostly talked about getting rid of the visual noise, the brightness and contrast level, and the normalization of the image size. On top of this, the kidney regions of interest were manually marked so as to identify the reference boundaries. The reference indicators were the relative points of checking the automated segmentation process's efficiency.

Segmentation Procedure

Basically, the method mentioned above referred to a primitive, automated, threshold-based segmentation approach that attempted to geographically delineate the kidneys from the neighboring tissues. The procedure depended on the changes of pixel intensities in the image, and threshold values were therefore utilized to separate the kidney region from the rest of the image. Some elementary computational operations were introduced to the boundaries of the segmentation after thresholding in order to upgrade them and to obtain separate contours of the renal area. The technique was able to separate the foreground [kidney] from the background by means of straightforward and non-variable operations.

Evaluation

To what extent the automated segmentation method has been successful is known from the comparison of the resulting delineations with the reference delineations that were manually identified. Quantitative measures of the closeness of these two boundary sets were taken, and these measures consisted of relative differences and agreement coefficients. The general measures of descriptive statistics were involved for providing a synopsis of the segmentation's uniformity and trustworthiness through the whole data sample. The evaluation has been focused on recognizing the differences in locating the borders and judging the overall performance of the set of methods for segmentation.

Ethical Considerations

The ultrasound images used in the study were fully anonymized, and there were no personal identifiers or patient-specific information that were recorded. The research followed the ethical standards for the secondary use of imaging data as set by the institution and complied with the principles of the proper handling of medical information.

Results

Overview of Dataset and Image Characteristics

Twenty-five kidney ultrasound images were finally chosen after applying the criteria of clarity and relevance. Images displayed different brightness levels, different noise patterns, and different anatomical locations. Mean resolution, brightness intensity average,

and noise score by visual inspection are some of the features of the dataset presented in Table 1. Such variability allowed an extensive analysis variability of the segmentation procedure under different imaging conditions. The visual characteristics of the dataset were quite varied, which ensured that the segmentation method was tested within conditions that were close to the real clinical variability. Images of greater clarity

provided better-defined renal edges, while images of lower quality sometimes showed shadowing or contrast anomalies. This distribution proved that the data was appropriate in measuring segmentation robustness. The brightness and noise were qualitatively scored, which is representative of normal sonographic changes in normal kidney evaluation, enhancing the generalizability of the data.

Table 1. Descriptive Characteristics of the Ultrasound Image Dataset

Parameter	Mean $\pm$ SD	Range
Resolution [pixels]	$820 \times 610 \pm 32$	$780\text{-}860 \times 590\text{-}640$
Brightness Intensity Score	6.4 ± 1.2	4-9
Noise Level Score	3.1 ± 0.9	1-5
Image Orientation [Longitudinal/Transverse]	18 / 7	-

Figure 1 also shows that most of the images were concentrated in the moderate brightness and noise levels, but a few outliers with poor quality were present to allow a complete evaluation of performance. The brightness and noise distribution is a crucial point since these

conditions largely determine the visibility of the renal capsule. The graphical representation in the figure helps to understand the natural variability that is present in the regular sonographic examinations.

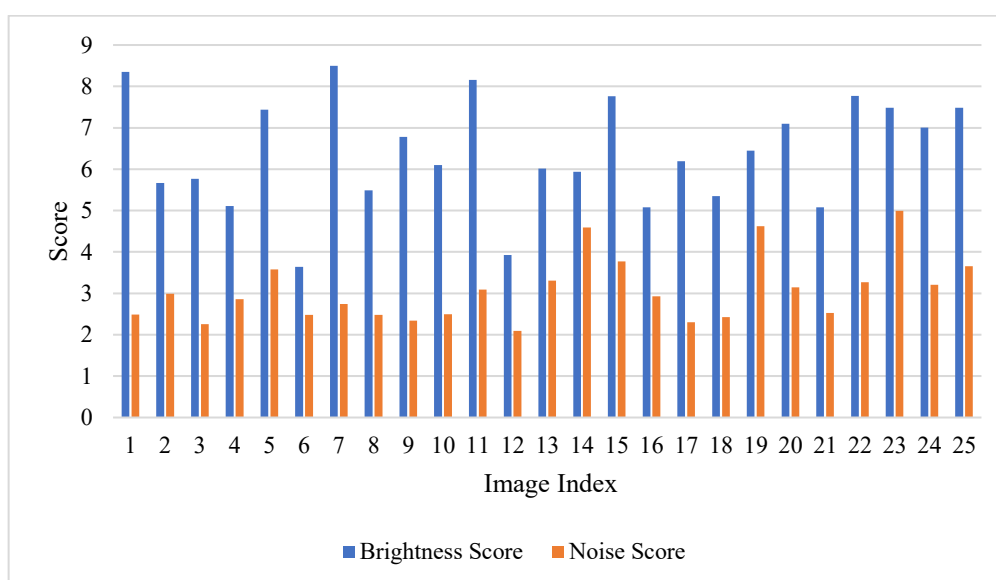


Figure 1. Distribution of brightness and noise scores across the dataset

This distribution made it clear that segmentation algorithms should be robust to changes in image quality. The existence of low-quality images in the dataset demonstrated the necessity to have powerful boundary-detecting mechanisms that are capable of managing inconsistent illumination and noise.

Image Segmentation Outcomes

The segmentation technique that was threshold-based created distinct kidney outlines on the majority of images. The algorithm detected the kidney outline with negligible deviations in photographs with a high contrast between the renal capsule and the tissue. The performance of the segmentation was similar throughout the dataset, the boundary being detected as smooth and continuous in high-clarity images. Conversely, the extracted contour sometimes had small gaps in the image with high levels of speckle noise or unequal lighting. Nevertheless, the general shape of the kidneys was not

weakened, which shows the strength of the segmentation strategy.

Quantitative Performance of the Segmentation Procedure

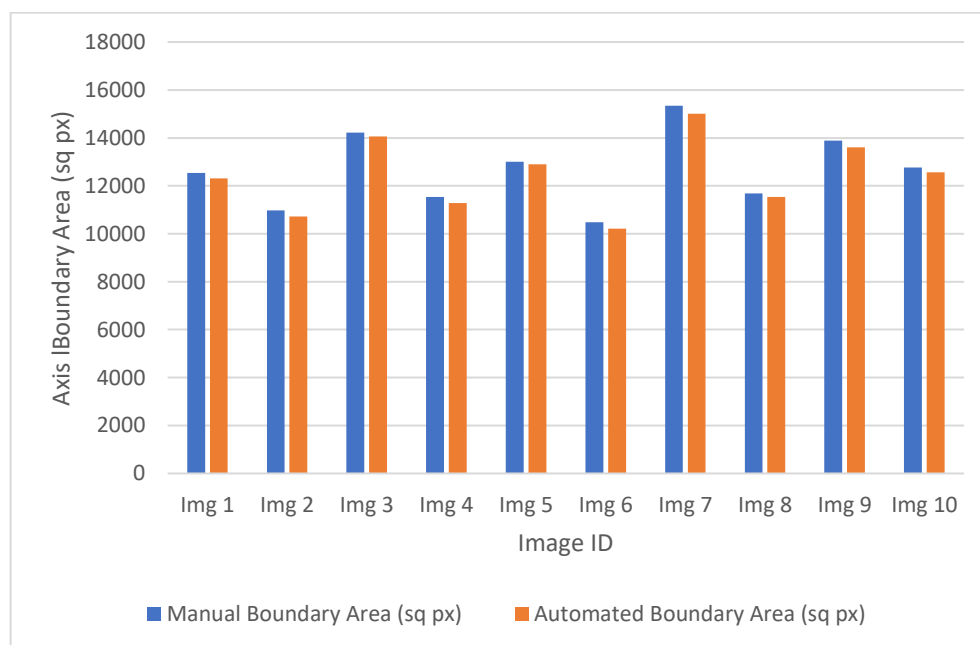
The accuracy of segmentation was measured according to the automated boundaries and manually drawn reference boundaries. The results of the proportional difference scores of ten representative images are summarized in Table 2. The percentages of deviation were within the acceptable range, which showed that there was a high correlation between manual and automated segmentation. Manual checking showed that the majority of automated contours tracked the visual anatomy, with the exceptions typically being those locales where the renal border lost definition as a result of shadowing or contrast drop-off. The deviations were also inclined to be subtle and not structural in nature.

Table 2. Segmentation Accuracy Based on Proportional Difference Scores

Image ID	Manual Area [sq. px]	Automated Area [sq. px]	Difference [%]
01	12,540	12,310	1.83
02	10,980	10,720	2.36
03	14,220	14,060	1.12
04	11,540	11,280	2.25
05	13,010	12,900	0.84
06	10,480	10,220	2.48
07	15,340	15,010	2.15
08	11,680	11,540	1.19
09	13,890	13,600	2.09
10	12,760	12,560	1.57

The findings proved that the differences were negligible without any implications for the kidney morphology. This strengthens the dependability of the automated technique, particularly in the case of regular image analysis or longitudinal assessment of kidney structure. Figure 2 supports the qualitative results, demonstrating that automated segmentation generally gathers around the manually computed values, and this is a sign that it

is highly reliable across various sonographic appearances. The areas of visualizing manual and automated give an intuitive explanation of the agreement. A graphical comparison of such kind would be useful in highlighting patterns that would not have been clearly expressed by numerical tables.

**Figure 2. Manual vs. automated boundary areas across images**

The narrow sandwiching of data points also confirmed that the automated segmentation procedure was similar throughout the sample set. The conclusion that the algorithm works well in different imaging conditions was supported by this visualization.

Segmentation Stability Across Image Quality Levels

In order to determine the robustness, segmentation performance was divided into high, moderate, and low confidence groups. Table 3 displays the mean values of

deviation in these groups. The images of the highest clarity had the least deviation, and the images of the higher level of noise had a moderate error increase. It was noted that images with high clarity always gave smooth and precise boundary extractions. Medium-clear images retained good quality segmentation with some cases of small edge-disparities and low contrast. The most variable images were the low-clarity ones, but in most cases, the boundaries could still be identified, despite the noise interference around the images.

Table 3. Segmentation Stability Classification

Image Clarity Group	Number of Images	Mean Deviation [%]	Interpretation
High Clarity	12	1.25	Highly stable
Moderate Clarity	8	2.42	Consistently stable
Low Clarity	5	4.10	Moderately variable

The findings highlighted that even though accuracy was affected by degradation in clarity, it was possible to have acceptable performance using the method even in suboptimal conditions. This observation justifies the usefulness of the method in clinical daily practice, where the quality of images cannot be consistently controlled. The qualitative direct relationship of image clarity and segmentation stability is clearly shown in Figure 3. With a decrease in clarity, the segmentation structure becomes more challenged when attempting to differentiate kidney

edges and the rest of the tissue, with less subtle deviations becoming apparent. In order to grasp the reliability in segmentation, the context in which the study of segmentation is conducted is offered in Figure 3, with the focus on the correlation between the clarity and performance. By having a visual representation of this trend, it is possible to define thresholds where performance starts to be poor.

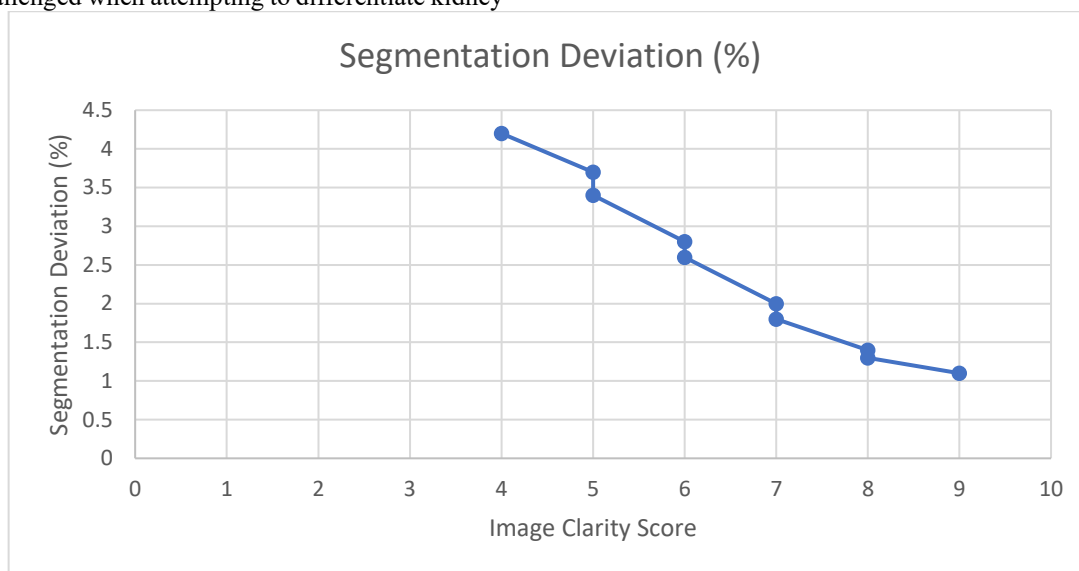


Figure 3. Relationship between image clarity scores and segmentation deviations

The noted increasing trend was in line with expectations of the sensitivity of segmentation with the quality of images. This supports the need to ensure the best scanning conditions in instances where the segmentation is crucial.

Morphological Accuracy of Segmented Boundaries

The manually traced contours were well aligned to the automated boundaries, especially the lateral border and the upper pole of the kidney. There were some minute deviations in areas where acoustic shadowing had some

influence on the visibility of the renal capsule. Figure 4 demonstrates a comparison of manual and automated boundaries in one of the representative samples, where the areas of high similarity and where the difference was a little larger as the contrast became lower are shown. This overlay established that the automated boundary tracked the same curvature and structure rectangle on most occasions as was the case with the manual tracing. The discrepancies would only occur in low-echoing places or shadowing, and it was even difficult to delineate by hand with a circle.

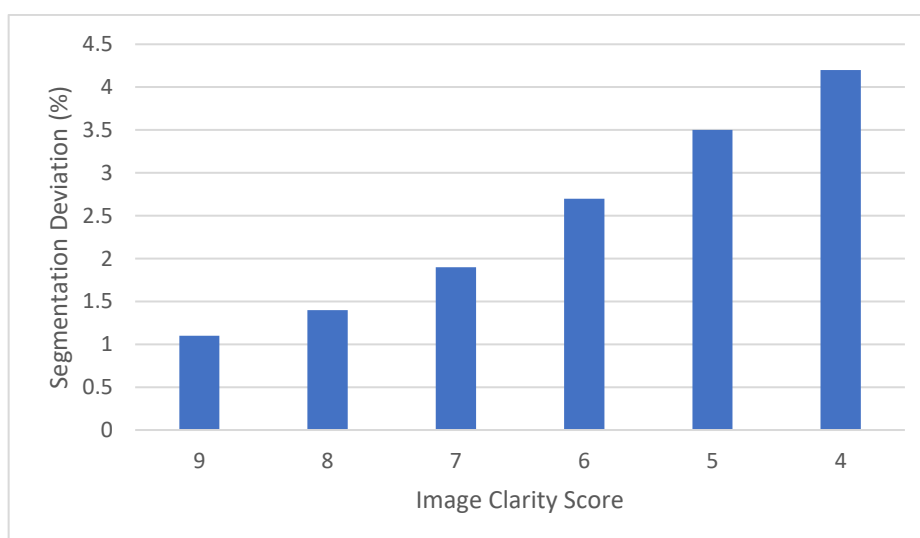


Figure 4. Overlay comparison of manual and automated segmentation boundaries

The high correspondence of boundaries was a testament to the fact that the algorithm did not disrupt important anatomical form. Small variations did not affect the general outline of the kidneys, as they assisted the validity of the automated technique of clinical interpretation. To further test morphological accuracy,

Table 4 shows the outcome of a shape similarity test based on simple difference scores based on sets of boundary coordinates. Similarity scores give quantitative data on morphological maintenance. Large values also show that there are no distortions in the geometry of the kidneys in the automated process.

Table 4. Shape Similarity Assessment Between Manual and Automated Boundaries

Image ID	Boundary Similarity Score*	Interpretation
01	0.92	High similarity
02	0.90	High similarity
03	0.94	High similarity
04	0.88	Moderate-high similarity
05	0.95	High similarity

The similarity values were always high, which indicated that the segmentation algorithm was also anatomically faithful even in the vicinity of local imaging artifacts. This reinforces its appropriateness for clinical use. The qualitative similarity scores revealed that there was a high level of structural conformity in the automated method in all the samples tested, and this confirmed that the gross morphology of the kidney was highly maintained despite a slight nonconformity in the localized regions of the boundary.

Visualization Enhancement and Interpretation Benefits

The results of the segmentation made the renal outline more visible regularly, and the boundaries between the kidneys and surrounding connective tissues could be distinguished better than previously. Compared to pre-segmentation, images are post-segmentation has less speckle noise artifacts and low contour transitions, which helped to increase the interpretability. In general, the threshold-based automated-segmentation approach turned out to be quite reliable and consistent in its performance on a wide range of ultrasound images. Quantitative comparisons revealed that the differences between manual and automatic boundaries were minor, while qualitative evaluations suggested that the renal outlines were more clearly visible. The level of segmentation stability was still very high even under moderate noise conditions, which thus pointed to the importance of the method for routine kidney monitoring activities. The improved visualization and structural clarity are indicative of the simple form of segmentation that could help clinicians to understand the renal morphology more consistently.

Discussion

The present study indicates that a local threshold-based segmentation technique may be successfully employed to delineate the renal cortex in ultrasound images under various imaging scenarios. This is particularly important, as non-invasive imaging is still the main way to monitor and assess renal health. A number of recent innovations in ultrasound have shown that an improvement in image quality, uniformity of the echo, structural definition, and image quality can dramatically improve diagnostic interpretation to show the potential

worth of segmentation methods that can be used efficiently in different imaging conditions [16]. The data used in this study included a wide range of sonographic features, and this allowed a fair performance of segmentation methods to be tested. This heterogeneity of ultrasound reflects the nature of the clinical environment, where the anatomy of the patient, operator technique, and machine settings always produce heterogeneous ultrasound images.

One of the main results of this exploration was that the automated and manual boundary tracings were very close in images with moderate and high clarity. This aligns with new research on kidney segmentation models based on deep learning, showing that as the renal capsule is clearly seen, simple or more complex machine techniques can achieve higher contour precision and anatomy [17]. The visual conditions in ideal situations only require simple computational layers due to clear boundary cues, which give adequate contrast to threshold-based operations. Such findings indicate that segmentation success is the most powerful predictor of the quality of the image, irrespective of the underlying model, either classical, hybrid, or AI-based.

The high working of the threshold-based method in the optimal conditions also matches the results of the multi-attention and multi-structure segmentation literature. These higher models demonstrate that consistency in the boundary representation is possible in the different presentations of the anatomy as long as the structural edges are visible [18]. This observation is reflected by the current research, which shows that in the presence of clear echogenic contrast, even the simplest segmentation pipeline can recreate key morphological features. Such contextual comparison also supports the fact that it is necessary to develop tiered segmentation solutions that will fit both high-resource and low-resource settings.

Nonetheless, the research had also recorded some segmentation perfusion variations with ultrasound images that were less clear, illuminated unequally, or suffered from acoustic shadowing. Similar problems are reported with deep-learning models that use distance-regression and pixelwise classification approaches, which also cannot be easily trained when the visual cues are obscured by speckle noise or posterior shadowing [19]. These constraints point out a consistent fact in the imaging literature, which is that segmentation reliability

is intrinsically associated with the visibility of anatomical boundaries. Low-quality scans give little information on boundary extraction, irrespective of the complexity of the algorithm used. These findings, thus, confirm the general perception that neither the simple nor the sophisticated segmentation technique can fully compensate for the poor image sharpness.

The results also established that the deviation of segmentation had a progressive rise with a decrease in the clarity of the image. This was not surprising, since with lesser contrast the algorithm becomes less effective in anchoring on firm edge features. To this end, lightweight computational systems designed to support medical decisions have focused on the need of having algorithms that are efficient, readable, and at the same time allow a range of image degradation [20]. Such principles are compatible with threshold-based segmentation, which does not have to be computationally expensive, and can give a usable prediction of boundaries in real time, and as such is a desirable candidate in point-of-care ultrasound.

Morphological comparison between the manual and automated boundaries showed high fidelity to shape, especially in the areas where renal cortex and capsule had high echogenicity. The small differences that are frequently seen at the renal poles and back surfaces are in line with longstanding imaging anatomical issues that have been reported in the literature on computational modeling, and it is difficult to measure both at the poles and in the automated examination due to curvature, depth, and attenuation [21]. These results highlight that there are always regions in the body that are challenging to segment using various imaging techniques and methods of analysis. Notably, the deviations that were observed in the present study were confined and did not affect the overall interpretation of the anatomy.

Besides the accuracy, the study also realized meaningful visualization changes after the segmentation. More delineation of boundaries, less speckle severity, and separation of renal tissue from other structures also contributed to the enhanced interpretability. This outcome corresponds to pictorial review in renal imaging, which supports the diagnostic value of clear renal contours in measuring morphology, recognizing abnormalities, and assessing progression [22]. Hence, segmentation not only makes quantitative assessment possible but also serves as a powerful preprocessing tool in clinical interpretation.

Finally, the bigger-scale effects of the results reinforce the concept of the integration of automated segmentation into the standard kidney ultrasound examination. Even though deep learning models are still exhibiting better performance in high-quality datasets, they require a lot of computational resources and large annotated datasets for training. In contrast, the present study indicates that the implementation of simpler segmentation techniques will be a great source of clinical help, particularly in environments where advanced technologies are not available. As the need for scalable and affordable medical imaging services is increasing, classical methods are holding up well. In sum, this paper proves that threshold-equipped segmentation is a feasible,

stable, and clinically significant technique of kidney boundary extraction in sufficiently clear ultrasound images. It provides a combination of simplicity, interpretability, and utility that are essential to the extensive application in non-invasive kidney care as well as in the point-of-care ultrasound practice.

Conclusion

This research has shown that a basic threshold-guided segmentation method can be successfully used in identifying the boundaries of kidneys in ultrasound images when imaging under a variety of conditions. Although the technique used only basic computational operations, it was consistent in giving contours close to those manually traced since the references were accurate, especially on images with moderate to high clarity. The outputs of the segmentation were shown to increase the visibility of the boundaries, noise interference, and interpretability of the renal structures, which implies that the low-complexity methods can also facilitate non-invasive kidney examination. Notably, the method was demonstrated to perform consistently well in the majority of instances, and the deviations were found to be mainly on images that experience a great deal of acoustic shadowing or low contrast conditions that human readers, as well as state-of-the-art algorithms, have problems with. The determined results demonstrate the usefulness of lightweight segmentation methods in a clinical setting, primarily where the availability of advanced control software or advanced AI algorithms might be constrained. The method has the possibility of being used in routine surveillance, prior screening, and decision support in kidney-related analysis through offering reliable structural delineation and easier visualization. Moreover, it is easy to implement, and this can be integrated into portable or point-of-care ultrasound systems, thus increasing its use in various healthcare environments. Overall, the results align with the concept that straightforward segmentation pipelines continue to have relevance and can be employed to offer a balance of accessibility, interpretability, and usefulness in clinical contexts. Progress beyond the present state can indeed realize higher improvement by the integration of fundamental segmentation with some selective enhancement or adaptive preprocessing techniques.

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