Journal of Pediatric Urology (xxxx) xxx xxx

Original Research

CurvAssist: An AI assisted pipeline for penile shaft segmentation/ curvature measurement in children with hypospadias

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Keywords
Hypospaias; Ventral curvature; Goniometer; Smart app goniometry; Artificial intelligence; Penile segmentation

Received 28 October 2025
Revised 26 January 2026
Accepted 9 March 2026
Available online xxx

Summary

Introduction
Accurate assessment of ventral curvature (VC) is critical in determining the type of VC correction. Unaided visual inspection (UVI) remains common but is prone to significant interobserver variability and error. Although smartphone app-based measurement (SAM) offers greater objectivity, it still relies on manual reference point selection. This study describes the development and evaluation of *CurvAssist*, an AI-assisted pipeline integrating deep learning–based segmentation for accurate, automated penile curvature measurement.

Methods
In step-1, a synthetic dataset of 250 images was generated from 3D phantom penile models with known ground-truth curvatures (0°–90°) under randomized lighting, angle, and background conditions. Penile shaft segmentation was achieved using a U-Net convolutional neural network. Curvature quantification employed a nonlinear least-squares circle-fitting algorithm using the Levenberg–Marquardt optimization to fit arc contours and calculate curvature angles geometrically. In step-2, the circle fitting algorithm's outputs were compared against SAM on clinical photographs (n = 7). Model performance was evaluated using Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, Mean Absolute Error (MAE), and Intraclass Correlation Coefficient (ICC).

Results
U-Net that analysed phantom 3D images (n = 250) achieved high segmentation accuracy with mean DSC 0.925 ± 0.021, IoU 0.910 ± 0.035, Precision 0.958, and Recall 0.947, providing a robust foundation for geometric quantification. The circle-fit algorithm estimated curvature with a MAE of 1.35°, representing a clinically negligible deviation from ground-truth. Comparison of AI-derived versus SAM-measured angles of clinical photographs (n = 7) demonstrated excellent agreement (ICC = 0.981).

Discussion
CurvAssist achieved a notable improvement and compares favourably with other emerging computational methods. While the AI-based applications have evolved to match the level of SAM measurements, they are likely to be more consistent when the model becomes robust avoiding human errors/ relying on manually selected reference points on SAM. *CurvAssist* should still be considered as a proof-of concept or technical feasibility study requiring further large-scale validation. The time required for segmentation and computation was not evaluated in this study.

Conclusion
CurvAssist can provide surgeons with objective, reproducible data to guide intraoperative decision-making, standardize surgical planning, and enhance multi-center research by minimizing interobserver variability. Future research should focus on prospective validation using a large dataset of intraoperative images, expanding the system to perform true 3D measurements from multiple views, and in developing a user-friendly real-time interface for seamless integration into the clinical workflow while addressing regulatory concerns on data handling and privacy.

https://doi.org/10.1016/j.jpurol.2026.105877

Introduction

Accurate assessment of ventral curvature (VC) is a critical step during hypospadias repair. [1,2]. Proper assessment and correction of VC is essential to prevent recurrent/residual curvature after hypospadias repair [3]. Mild to moderate curvature, can be easily underestimated on unaided visual inspection (UVI) alone [4,5]. The burden of inadequate curvature correction is impacted by variability in curvature assessment methods, absence of standardized protocols and lack of validated tools [6,7]. The long-term negative impact of residual curvature in adulthood remains underestimated due to limited longitudinal data.

A large proportion (70–90%) of pediatric urologists report confidence in their naked-eye assessments of penile curvature [8]. However, several clinical studies have shown that UVI is prone to significant error when compared with objective curvature measurement techniques [4,6–8]. Although standard goniometry (SG) using a hand-held device and smartphone app-based measurement (SAM) are often reported, some studies have shown that they are also not as accurate due to human interface [9].

Previous research has emphasized the need for objective penile curvature (PC) assessment during hypospadias repair and has highlighted the potential for human error in conventional techniques, underscoring the value of automated computer-based approaches [10]. To date, only a few studies have explored computer-assisted methods for objective PC measurement [11,12].

In this study we developed "*CurvAssist*" an artificial intelligence (AI) assisted pipeline for penile shaft segmentation and curvature measurement based on 3D models. The system incorporates a novel circle fitting algorithm to minimize errors related to reference point selection. We also applied this pipeline to intraoperative human photographs to evaluate whether the angles measured by our AI-assisted model correlate with those obtained using conventional methods, such as smartphone app—based goniometry.

Methods

In step-1, a synthetic dataset of 250 images of base 3D virtual model of a penis was created using a set of anonymized clinical photos (Fig. 1). A custom algorithm was then used to procedurally create a library of 3D models with precisely known ground-truth curvatures ranging from 0° to 90°. These 3D models were used to create a dataset of 2D images. To ensure resilience and generalization to real-world conditions, renderers added a variety of lighting conditions (colour, intensity), randomized virtual camera positions (angle, distance), and intricate, textured backgrounds. Each synthetic image was created using the known curvature angle and a pixel-perfect ground-truth segmentation mask. The final dataset (n = 250) was used to create training (80%), validation (10%), and testing (10%) sets.

Images underwent a standardized preprocessing pipeline before being fed to the network. This process includes resizing of images 256 × 256 pixels, normalization by scaling the pixel values to [0, 1] floating-point range and Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance the visibility of the penile shaft boundaries. To prevent getting overfitting and improve overall generalization, data augmentation was applied during training. This included random transformations such as rotations, flips, scaling, brightness, contrast and non-rigid elastic deformations to simulate the variability of soft biological tissue.

The model consists of contracting encoder path to capture context and a symmetric expansive decoder path for localization. Skip connections between the encoder and decoder paths allow the Neural network to combine high-level semantic information with low-level of spatial details which enables highly accurate boundary retrieval. The final layer of the network used a sigmoid activation function to produce a probability map, which was used to get the final binary segmentation mask.

The model was trained using a composite loss function that was a weighted sum of Binary Cross-Entropy (BCE) and Dice loss. This provided a balance between accuracy and overlap optimization. The Adam optimizer was used with an initial learning rate of 1e-4 and cosine annealing schedule to update the Neural network's weights.

The quantification algorithm processes the U-Net's output mask (Fig. 2). A contour finding algorithm was applied to the segmented binary mask to extract the ordered list of pixels outlining the penile shaft and the points corresponding to the primary curved edge are isolated. The two endpoints of the arc are defined as the pair of points on the contour with the maximum Euclidean distance between them and this distance represents the chord length.

We implemented the Nonlinear Least-Squares Circle Fitting (Fig. 3) by finding the parameters (center (x_c, y_c) and radius r) of a circle that best fits the extracted arc points. This is accomplished by iteratively solving a non-linear

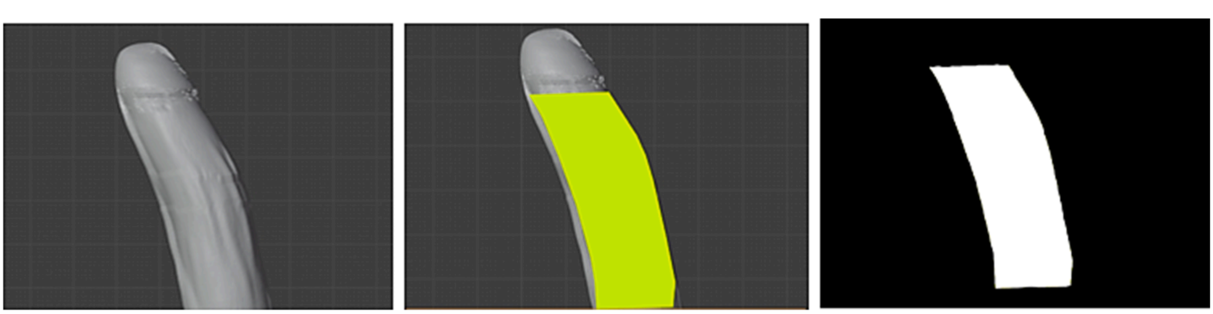

Fig. 1 Penile shaft Segmentation of synthetic 3D model.

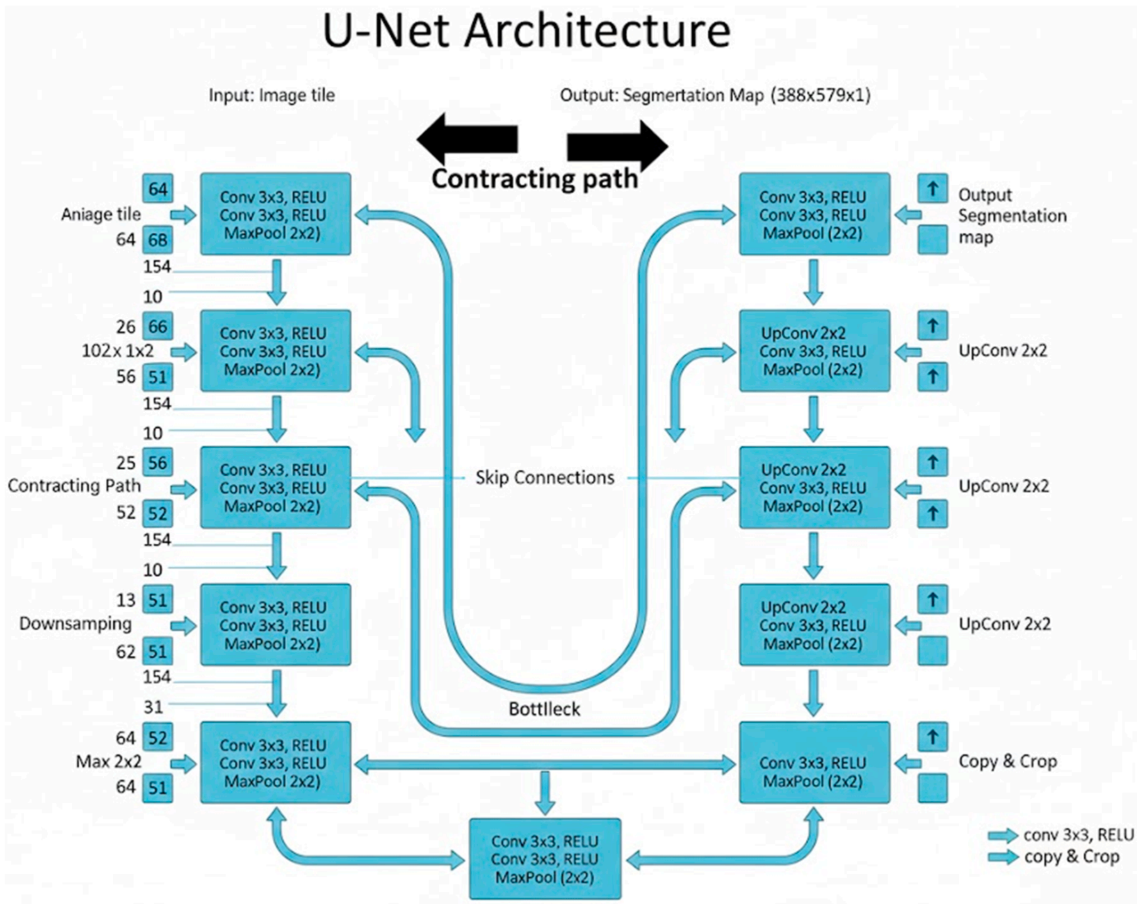

Fig. 2 Architecture of U-Net Deep Learning model.

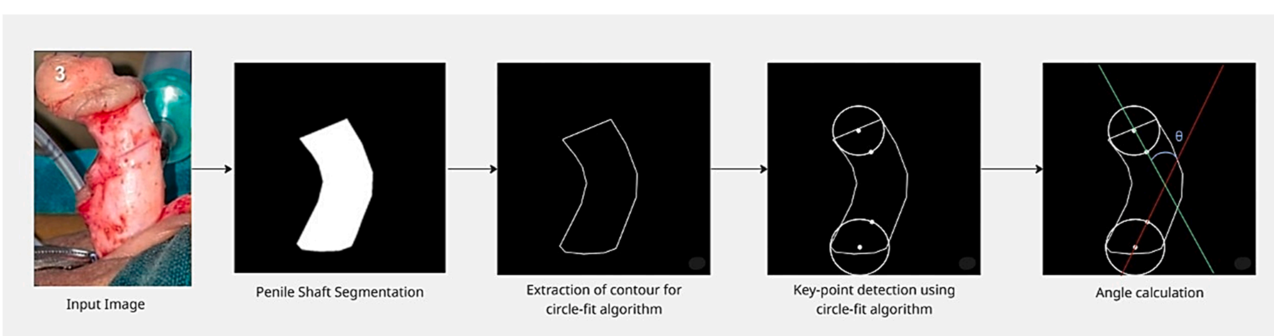

Fig. 3 Circle fitting algorithm for penile curvature measurement based on clinical intra-operative photographs (the intra-operative image was of a degloved penis before urethral plate division-photograph was taken keeping camera in line with the lateral profile of penile shaft).

optimization problem using the Levenberg—Marquardt algorithm and minimizing the sum of squared geometric distances between each point on the arc and the diameter of the circle. This global fitting method is resistant to small segmentation flaws and local noise. After the ideal circle is discovered, the curvature angle is the center angle subtended by the endpoints of the arc. The angle between the two endpoints, which are represented by vectors drawn from the center of the circle, is determined using the dot product. Arc length, chord length, and radius of curvature ($k = 1/r$) can all be used to create a set of geometric metrics.

In step-2, the circle fitting algorithm's outputs were compared against SAM on clinical photographs ($n = 7$). The intraoperative images were of a degloved penis before urethral plate division. Photograph was taken keeping the camera in line with the lateral profile of the penile shaft. The U-Net architecture was used to perform semantic segmentation of penile shaft from penile images ($n = 7$).

Table 1 Angle of curvature measured in degrees by AI and SAM.

	AI (CurvAssist)	SAM (Angulus)
Patient 1	42.15	41.87
Patient 2	20.55	22.07
Patient 3	55.50	55.10
Patient 4	35.21	37.56
Patient 5	25.43	26.71
Patient 6	26.98	27.43
Patient 7	32.09	31.11

The pipeline was evaluated on a held-out test set. Segmentation performance was assessed using Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision and Recall scores. The accuracy of angle quantification algorithm was evaluated using Mean Absolute Error (MAE) and Interclass Correlation Coefficient (ρ) values to compare the predicted angles against the known ground-truth values.

Results

U-Net model that analysed phantom 3D images ($n = 250$) achieved high segmentation accuracy with mean DSC 0.925 ± 0.021, IoU 0.910 ± 0.035, Precision 0.958 ± 0.029, and Recall 0.947 ± 0.031, providing a robust foundation for geometric quantification. Table 1 depicts the actual values obtained by the AI model and SAM model on clinical photographs ($n = 7$).

The circle-fit algorithm demonstrated a very good accuracy in quantifying the curvature angle. The Mean Absolute Error (MAE) was found to be 1.35° which is a clinically insignificant margin of error. The Intraclass correlation coefficient (ρ) of 0.981 indicated an excellent positive correlation between the AI estimated and actual angles.

Discussion

Recurrent or residual curvature following hypospadias repair is often attributed to inadequate correction of ventral curvature (VC) [1,2] or improper assessment of the deformity [3]. Several studies have shown that UVI is inferior to objective methods of curvature measurement [4,6–8] and have advocated for automated [13,14] approaches using smart phones [15] or computer models. While previous studies have focussed on 3D models [11,12], out study extended to apply the pipeline model to intraoperative photographs. We aimed to evaluate whether the curvature angles calculated by this novel circle-fitting algorithm, an AI-assisted pipeline, correlate with conventional measurement techniques, such as SAM, which are widely used in clinical practice [4,6,8].

Our AI model, *CurvAssist*, successfully demonstrated a fully automated pipeline that integrates deep learning–based segmentation with a novel circle-fitting algorithm to quantify penile curvature with high precision. The achieved mean absolute error (MAE) of 1.35° represents a notable improvement over the existing standard of care and compares favourably with other emerging computational methods. Abbas et al. [16] standardised the steps of SAM and Fernandez et al. [17] used a semi-automated algorithm with digital images to standardize PC assessment and reduce subjectivity. Other authors proposed a digital measurement technique based on the Cobb scoliosis angle [18]. 3D printing and AI-based algorithms have taken high-accuracy curvature measurement to the next level. While the AI-based applications have evolved to match the level of SAM measurements, they are likely to be more consistent when the model becomes robust avoiding human errors that are possible while computing angle based on manually selected lines on SAM. The future of VC measurement is therefore likely to be an AI-based smart phone application, which could measure angle of the degloved penis near instantaneously during hypospadias repair.

Table 2 compares existing VC measurement AI models and the present study. Abbas et al. [11], utilized deep learning architectures such as U-Net or DeepLabV3 to generate binary masks of the penile shaft, followed by a morphological thinning algorithm to extract a one-pixel-wide centre line. A mathematical function, typically a higher-order polynomial, was then fitted to this centre line to derive curvature values. However, skeletonization algorithms are highly sensitive to minor segmentation noise, and irregular boundaries can lead to unstable and inaccurate angle estimations.

Baray et al. [12], proposed a landmark-based approach using a multi-stage pipeline. After segmentation, a specialized architecture such as the High-Resolution Network (HRNet) identified predefined anatomical key points on the penile shaft. The curvature angle was then calculated geometrically from the vectors connecting these landmarks. The accuracy of this technique, however, depends heavily on consistent and precise localization of a limited number of points, which can be challenging in cases of poor image quality or reduced anatomical visibility.

In contrast, *CurvAssist* employs a global geometric fitting strategy to overcome the limitations of previous methods. The system integrates U-Net segmentation with a robust circle-fitting algorithm to quantify curvature in a fully automated manner. This approach achieved higher

Table 2 Conceptual comparison of curvature quantification algorithms.

Feature	Skeletonization/Polynomial Fit [11]	Landmark Detection [12]	Circle-Fit (Current study)
Underlying principle	Polynomial fitting to centreline	Discrete point detection	Global geometric circle fitting
Robustness to noise	Low	Medium	High
Dependence on landmarks	Low	High	Low
Geometric intuition	Mathematical coefficients	Vector angles	Radius, central angle, arc length

Please cite this article as: Babu R et al., CurvAssist: An AI assisted pipeline for penile shaft segmentation/ curvature measurement in children with hypospadias, Journal of Pediatric Urology, https://doi.org/10.1016/j.jpurol.2026.105877

accuracy than subjective methods currently used in clinical settings. Unlike skeleton-based models, which are prone to boundary noise, our global fitting algorithm averages out minor segmentation imperfections. Compared with landmark-based models that rely on the exact placement of discrete points, our algorithm is more resilient to anatomical and photographic variability because it utilizes information from the entire curve. Moreover, the model provides a richer geometric description of the deformity than polynomial coefficients.

The primary limitation of this study lies in its reliance on a synthetic dataset for training and validation. Additionally, the clinical 2D images processed by the AI model may still be affected by parallax errors [9,19] inherent to human photography. Real-time segmentation in the operating room could mitigate such issues. The time required for segmentation and computation was not evaluated in this study, and further optimization is needed to enable real-time curvature assessment. We have only tested this model on a very small number of clinical photographs. Further larger studies are warranted to validate the findings of this study. In addition, the clinical implications of AI based curvature measurement, like what percentage of patients actually benefitted from applying this method, need further exploration. In that context the current study should be considered as a proof-of concept or technical feasibility study requiring further large-scale validation.

Despite the above limitations the potential future clinical implications of AI-based curvature assessment are substantial. *CurvAssist* can provide surgeons with objective, reproducible data to guide intraoperative decision-making, standardize surgical planning, and enhance multi-center research by minimizing interobserver variability. Future research should focus on prospective validation using a large dataset of intraoperative images, expanding the system to perform true 3D measurements from multiple views, and developing a user-friendly real-time interface for seamless integration into the clinical workflow while addressing regulatory concerns on data handling and privacy.

Conclusions

CurvAssist provides an accurate, objective, and fully automated tool for penile curvature assessment. It holds potential to standardize intraoperative VC measurement, minimize interobserver variation, and support decision-making during hypospadias repair. Larger clinical validation studies are warranted.

IEC approval

IEC-NI/24/JUL/96/116.

Funding

Nil.

Conflict of interest

Nil.

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