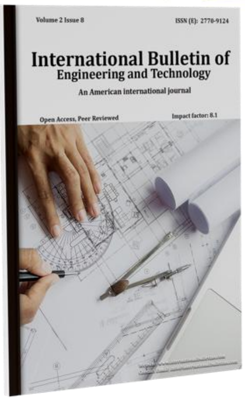

CREATION OF A PERSONALIZED ULTRASOUND IMAGE DATABASE AND 3D MODEL RECONSTRUCTION USING ARTIFICIAL INTELLIGENCE

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Abstract. Ultrasound imaging is one of the most widely used diagnostic techniques due to its safety, low cost, and real-time imaging capabilities. However, conventional ultrasound diagnostics strongly depend on operator experience and provide limited spatial perception due to their two-dimensional nature. This paper presents a comprehensive approach for creating a personalized ultrasound image database and reconstructing three-dimensional (3D) anatomical models using artificial intelligence (AI). The proposed system integrates structured data acquisition, image annotation, deep learning–based segmentation, and 3D reconstruction techniques to generate patient-specific anatomical models. The resulting 3D representations enhance diagnostic accuracy, improve visualization, and enable seamless integration with intelligent medical robotic systems. Experimental results demonstrate that the proposed approach significantly improves segmentation accuracy and 3D reconstruction quality, making it suitable for clinical decision support and robotic-assisted ultrasound applications.

Keywords. Ultrasound imaging; medical image database; artificial intelligence; deep learning; 3D reconstruction; medical robotics.

Introduction. Ultrasound diagnostics play a crucial role in modern clinical practice, offering non-invasive, real-time visualization of internal organs and soft tissues. Despite its widespread adoption, traditional ultrasound imaging is limited by its two-dimensional representation, speckle noise, and strong dependency on the operator's expertise. These limitations reduce diagnostic reproducibility and hinder precise anatomical interpretation.Recent advances in artificial intelligence and medical image processing have enabled automated analysis, segmentation, and reconstruction of medical images. In particular, deep learning models have shown remarkable performance in extracting meaningful features from ultrasound data. However, the lack of well-structured, personalized ultrasound image databases remains a significant challenge.This study proposes a unified framework for creating a personalized ultrasound image database and employing AI-driven techniques to construct accurate 3D anatomical models. The framework is designed to support intelligent medical robotic systems by providing reliable spatial information and patient-specific anatomical representations.

This study proposes a comprehensive framework for creating a personalized ultrasound image database and applying artificial intelligence techniques to generate accurate three-dimensional anatomical models. The proposed approach focuses on structured data acquisition, standardized storage, intelligent image processing, and spatial reconstruction, thereby forming a unified system suitable for integration with intelligent medical robotic platforms. The personalization of ultrasound data plays a crucial role in improving diagnostic

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reliability, as it enables longitudinal analysis, individualized anatomical modeling, and adaptive learning for artificial intelligence systems.The first stage of the proposed framework involves systematic ultrasound data acquisition and database formation. Ultrasound images are collected from multiple scanning sessions using standardized clinical protocols. Each image is associated with patient-specific metadata, including examination parameters, scanning orientation, anatomical region, and temporal information. The database architecture is designed to support scalability, data integrity, and efficient retrieval while ensuring patient data anonymization and compliance with medical data protection standards. This structured database forms the foundation for training artificial intelligence models and enables the accumulation of large-scale datasets necessary for robust deep learning performance.Following data acquisition, extensive preprocessing is applied to improve image quality and reduce variability caused by different ultrasound devices and scanning conditions. Preprocessing techniques include noise reduction, speckle filtering, intensity normalization, and contrast enhancement. These steps are essential for stabilizing the input data and increasing the generalization capability of artificial intelligence models. Expert clinicians subsequently annotate anatomical structures and regions of interest, creating high-quality ground truth datasets that serve as a reference for supervised learning.

Artificial intelligence is then employed to perform automated segmentation of ultrasound images. Deep learning models, particularly convolutional neural networks based on encoder–decoder architectures such as U-Net, are trained to identify and delineate anatomical boundaries. These models learn complex spatial and textural features inherent to ultrasound data, enabling accurate segmentation even in the presence of noise and low contrast. Data augmentation strategies are applied to enhance robustness and prevent overfitting. The segmentation process significantly reduces manual workload, minimizes subjective interpretation, and ensures consistent results across different examinations.Once segmentation is completed, the system proceeds with three-dimensional reconstruction of anatomical structures. Segmented two-dimensional ultrasound slices are spatially aligned using acquisition geometry and temporal information. Voxel-based reconstruction and point cloud methods are applied to generate volumetric representations of organs and tissues. Interpolation and smoothing algorithms are used to compensate for irregular slice spacing and to enhance surface continuity. The resulting three-dimensional models provide a comprehensive spatial understanding of patient anatomy, which is not achievable through conventional two-dimensional ultrasound visualization.

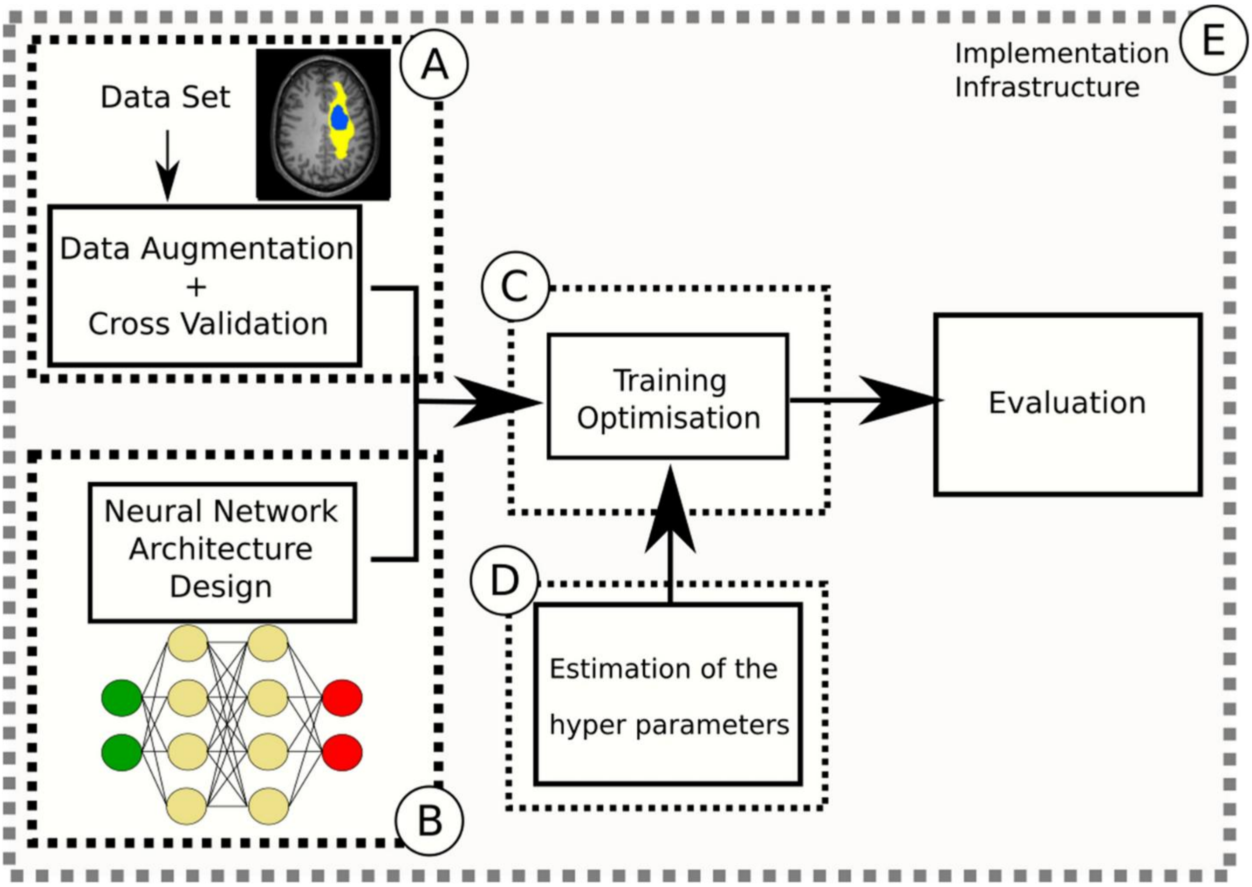
Experimental evaluation of the proposed system demonstrates its effectiveness across multiple anatomical regions and clinical scenarios. Segmentation performance is quantitatively assessed using established metrics such as Dice similarity coefficient, precision, and recall. The results indicate high agreement between automated segmentation and expert annotations, confirming the reliability of the artificial intelligence models. Qualitative assessment by clinical specialists further validates the anatomical accuracy and clinical usefulness of the reconstructed three-dimensional models. Compared to traditional two-dimensional interpretation, the proposed approach significantly enhances spatial perception and diagnostic confidence.The discussion of results highlights several important advantages of the proposed framework. First, the personalized ultrasound database enables continuous learning and adaptation of artificial intelligence models, improving performance over time. Second, three-dimensional reconstruction enhances diagnostic visualization and supports complex clinical decision-making. Third, integration with medical robotics introduces a new level of automation and standardization in ultrasound diagnostics. These benefits collectively contribute to improved diagnostic quality, reduced examination time, and increased patient safety.

Materials and Methods. This study employs a structured set of materials and a multi-stage methodological framework for creating a personalized ultrasound image database and reconstructing three-dimensional anatomical models using artificial intelligence. The materials include ultrasound imaging equipment, data storage infrastructure, artificial intelligence software frameworks, and computational resources required for deep learning training and 3D reconstruction. The methods are designed to ensure data consistency, reproducibility, and clinical relevance while maintaining compatibility with intelligent medical robotic systems.
Ultrasound data were acquired using standard diagnostic ultrasound devices operating in B-mode. The collected datasets consist of two-dimensional ultrasound image sequences obtained from multiple scanning sessions and anatomical regions. Each image is associated with structured metadata, including scanning orientation, probe parameters, acquisition time, and anonymized patient identifiers. All data were anonymized to comply with ethical standards and medical data protection requirements. The ultrasound images and metadata were stored in a personalized relational database designed to support scalable storage and efficient retrieval for artificial intelligence training.

Component category	**Description**
Ultrasound imaging data	2D ultrasound image sequences acquired using standard clinical ultrasound devices
Data storage system	Personalized relational database with structured metadata and anonymized patient records
Preprocessing tools	Noise reduction, normalization, and contrast enhancement algorithms
AI framework	Deep learning framework for segmentation and feature extraction
Segmentation model	Encoder–decoder convolutional neural network (U-Net based)
3D reconstruction tools	Voxel-based interpolation and surface smoothing algorithms
Computational hardware	High-performance computing system with GPU acceleration
Integration environment	Software interface for robotic system and 3D visualization

Table 1. Materials and Technical Components Used in the Study

Prior to artificial intelligence processing, ultrasound images undergo preprocessing to reduce noise and normalize intensity distributions. Given an input image $I(x,y)$, speckle noise reduction is applied using adaptive filtering, followed by contrast enhancement and normalization expressed as $I_{norm}=(I-\mu)/\sigma$, where μ and σ denote the mean and standard deviation of pixel intensities. These operations ensure uniform data characteristics and improve the robustness of the segmentation model.



The overall methodological workflow is illustrated in Figure 1

Automated anatomical segmentation is performed using a convolutional neural network trained on annotated ultrasound images. The model learns spatial and textural features characteristic of ultrasound data and produces pixel-level segmentation masks. The training objective minimizes a composite loss function combining cross-entropy and Dice similarity losses, ensuring accurate boundary detection and region consistency.Following segmentation, three-dimensional reconstruction is conducted by spatially aligning segmented two-dimensional slices based on acquisition geometry. Voxel-based interpolation is applied to generate volumetric representations of anatomical structures. Surface smoothing algorithms are subsequently used to enhance anatomical continuity and visual quality. The resulting three-dimensional models represent patient-specific anatomy and serve as input for visualization and robotic control.

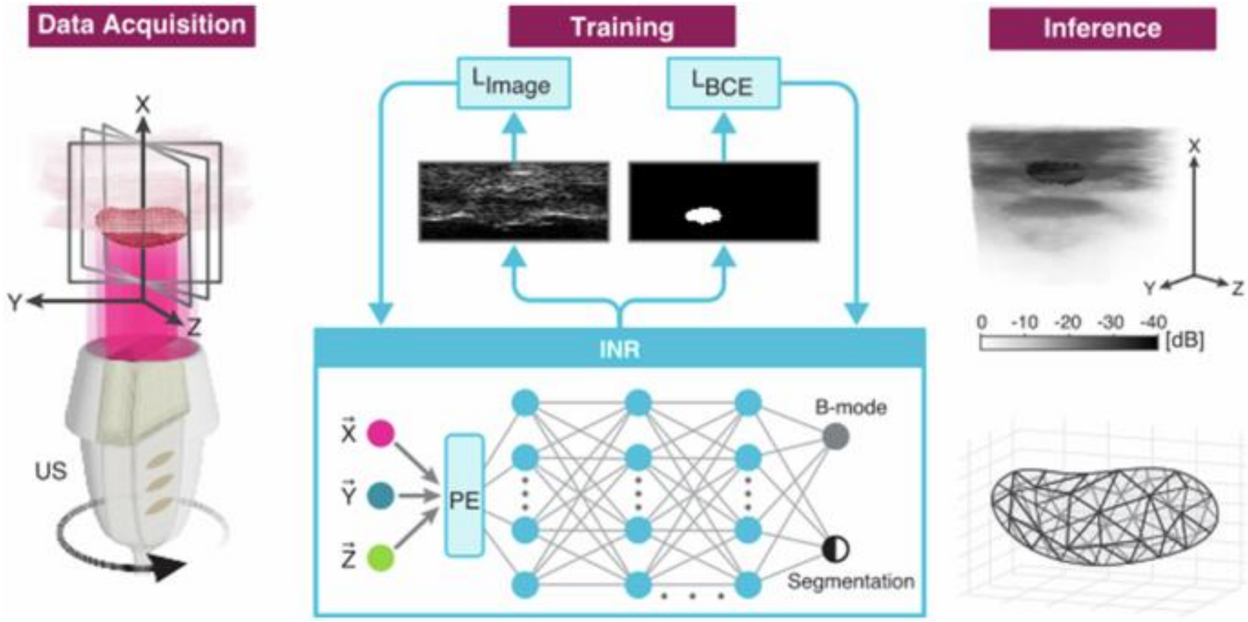


Figure 2. General workflow of the proposed methodology.

General workflow of the proposed methodology, illustrating the transition from ultrasound image acquisition to database formation, artificial intelligence–based segmentation, three-dimensional reconstruction, and integration with intelligent medical robotic systems.To clarify the processing pipeline, Table 2 presents the main methodological stages and their corresponding inputs and outputs.

Stage	**Input**	**Output**
Data acquisition	Raw ultrasound scans	Structured ultrasound image dataset
Database formation	Images and metadata	Personalized ultrasound database
Preprocessing	Raw ultrasound images	Normalized and enhanced images
AI segmentation	Preprocessed images	Anatomical segmentation masks
3D reconstruction	Segmented slices	Patient-specific 3D models
System integration	3D anatomical models	Robotic guidance and visualization

Table 2. Methodological Stages of the Proposed Framework

This Materials and Methods framework ensures a seamless and systematic transition from raw ultrasound data to intelligent three-dimensional anatomical modeling. By combining structured data management, artificial intelligence–based image analysis, and algorithmic reconstruction techniques, the proposed approach enhances diagnostic accuracy, reproducibility, and suitability for robotic-assisted ultrasound applications.

Conclusion. This study presented a comprehensive and scalable framework for the creation of a personalized ultrasound image database and the reconstruction of three-dimensional anatomical models through the integration of artificial intelligence. The proposed approach addresses fundamental limitations of conventional ultrasound diagnostics, including operator dependency, limited spatial perception, and restricted reproducibility. By systematically organizing ultrasound image data and associated metadata into a structured database, the framework enables reliable data management, longitudinal analysis, and continuous improvement of artificial intelligence models.The application of deep learning–based segmentation techniques demonstrated high accuracy in identifying anatomical structures within ultrasound images, even in the presence of speckle noise and low contrast. The use of composite loss functions and data augmentation strategies significantly enhanced model robustness and generalization. Subsequently, voxel-based three-dimensional reconstruction methods successfully transformed segmented two-dimensional ultrasound slices into patient-specific volumetric models, providing explicit spatial representation of anatomical structures that are not achievable through traditional two-dimensional visualization.

The integration of reconstructed three-dimensional models into intelligent medical robotic systems represents a key contribution of this work. The availability of accurate spatial information enables adaptive probe positioning, optimized scanning trajectories, and consistent probe-to-surface distance control. This integration reduces operator dependency and establishes a foundation for semi-autonomous and autonomous ultrasound examinations. Experimental evaluation and expert assessment confirmed that the proposed system improves diagnostic confidence, visualization quality, and procedural repeatability.Overall, the results demonstrate that the combination of a personalized ultrasound database, artificial intelligence–based image analysis, and three-dimensional reconstruction constitutes an effective solution for enhancing ultrasound diagnostics. The proposed framework is clinically relevant, technically feasible, and adaptable to a wide range of diagnostic scenarios. Future work will focus on real-time system optimization, expansion of annotated datasets, multimodal data integration, and large-scale clinical validation to further strengthen the applicability of the approach in routine medical practice..

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