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Multimodal Deep Learning for Enhanced Segmentation of Histotripsy Ablation Zones

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Abstract- This research presents histotripsy is a non-invasive ultrasound technique used for precise tissue ablation, showing promise in treating conditions like kidney tumors. This project proposes a deep learning-based segmentation system using a Convolutional Neural Network (CNN) with a ResNet-18 backbone to identify ablated regions in ultrasound images automatically. The system is trained on phantom images and uses digital photographs as ground truth. In addition to image segmentation, the system overlays segmented zones, counts treatment pulses, and supports real-time monitoring significantly improving speed, accuracy, and clinical decision- making.

Keywords: Histotripsy, Ultrasound Imaging, Tissue Ablation, Deep Learning, Image Segmentation

I. INTRODUCTION

With the increasing adoption of non-invasive treatment methods in modern medicine, histotripsy has emerged as a promising ultrasound-based technique for mechanically ablating unwanted tissues without the use of heat or invasive instruments[1]. This method uses focused acoustic pulses to generate bubble clouds that precisely destroy targeted tissues, making it especially valuable in treating conditions like kidney tumors [2], [10]. However, a critical challenge in clinical application lies in accurately identifying and monitoring the ablation zones during and after the procedure. Traditional ultrasound image analysis is limited by low contrast, speckle noise, and complex tissue structures, which make it difficult to reliably delineate treated regions [8], [5]. Manual segmentation, though common, is labor-intensive, subjective, and unsuitable for real-time clinical use [3],[4].

This project introduces an intelligent, automated solution that leverages deep learning specifically a Convolutional Neural Network (CNN) with a ResNet-18 backbone for segmenting histotripsy-affected regions in ultrasound images. By integrating this model with real-time visualization and pulse count features, the system enhances treatment monitoring, reduces dependency on manual interpretation, and improves diagnostic consistency. While conventional methods rely heavily on predefined features and expert input[6] [7], this deep learning framework learns directly from annotated image data, enabling it to handle diverse imaging conditions and complex tissue variations. The proposed system not only streamlines the segmentation process but also sets the stage for smarter, faster, and more reliable image-guided therapeutic workflows in ultrasound-based interventions [9], [10].

II. OBJECTIVE

To design and implement a deep learning-based segmentation system for histotripsy- treated ultrasound images that enables accurate, real-time identification of ablation zones. The system aims to automate the segmentation process, reduce reliance on manual interpretation, and enhance clinical decision-making by integrating image preprocessing, CNN-based classification, and post-processing techniques. It also supports real-time visualization by overlaying the segmented regions and counting the number of applied ultrasound pulses.

Problem Statement

Ultrasound image segmentation in histotripsy procedures remains a challenging task due to the poor quality of ultrasound images, which often suffer from low contrast and speckle noise. Manual segmentation, which is still widely used, is time-consuming, inconsistent, and prone to human error. Traditional image processing techniques and early-stage machine learning models lack the precision and adaptability needed for accurate segmentation across different imaging conditions. Moreover, current systems do not offer real-time analysis or automation, which delays critical clinical decision-making. Therefore, there is a strong need for an intelligent, automated system that can accurately segment ablation zones in real time, ensuring consistency, speed, and reliability in non-invasive ultrasound-guided treatment

Related Work

With the growing interest in non-invasive therapeutic techniques, histotripsy has gained significant attention as a revolutionary ultrasound-based tissue ablation method. Researchers have explored various image processing techniques to accurately detect and assess ablation zones, particularly using ultrasound imaging, which is challenged by noise, low contrast, and structural complexity. Several early studies relied on traditional segmentation methods, such as thresholding and edge detection, but these approaches were often sensitive to imaging artifacts and lacked robustness across diverse datasets.

To overcome these challenges, recent research has focused on leveraging deep learning techniques for medical image segmentation. For instance, Ronneberger et al. introduced the U- Net architecture, which became a foundational model for biomedical image segmentation due to its encoder-decoder structure and use of skip connections for preserving spatial information. In the context of histotripsy, Lundt et al. demonstrated a high-speed, electronically-steered ablation approach and emphasized the need for accurate imaging feedback, which motivated the integration of automated segmentation systems. Similarly, Xu et al. investigated histotripsy's therapeutic applications and highlighted the critical role of real-time monitoring in ensuring treatment efficacy.

Additional studies by Duryea et al. and Ponomarchuk et al. addressed the optimization of lesion formation and the challenges posed by residual cavitation nuclei and large hematomas, respectively. While their focus remained on ablation quality and technique, the limitations in manual image interpretation were acknowledged, supporting the case for AI-powered tools.

Furthermore, recent advancements in convolutional neural networks, especially ResNet-based models, have shown promise in improving segmentation accuracy, even in low-quality ultrasound images. Collectively, these contributions underscore the growing necessity for intelligent, real-time, and noise-resilient segmentation frameworks that enhance clinical decision-making and therapeutic outcomes in histotripsy procedures.

Existing System

In traditional medical image analysis, particularly in histotripsy-based ultrasound procedures, segmentation of ablated tissue regions is typically performed manually by medical experts. This process involves identifying and outlining the treated areas based on visual interpretation of the ultrasound images. However, manual segmentation is time-consuming, subjective, and prone to inter-observer variability, which affects consistency and accuracy. Additionally, ultrasound images often suffer from low contrast, speckle noise, and anatomical complexity, further complicating the identification of ablation zones.

Conventional segmentation techniques, such as thresholding, edge detection, or basic clustering algorithms, are limited in their ability to accurately process noisy and low-quality images. Although some machine learning models have been introduced, they rely heavily on handcrafted features and perform poorly across diverse datasets. These existing methods lack real-time processing capabilities and do not scale well in clinical environments where quick and accurate treatment assessment is essential. As a result, there is a clear need for an advanced, automated system capable of delivering fast, reliable, and accurate segmentation results in real time.

Proposed System

The proposed system leverages deep learning to automate and enhance the segmentation of ablated tissue regions in ultrasound images obtained during histotripsy procedures. By utilizing a Convolutional Neural Network (CNN) with a ResNet-18 architecture, the system is capable of learning spatial and textural features directly from image data, eliminating the need for manual feature extraction. This model is trained on a curated dataset of histotripsy-treated ultrasound images, allowing it to accurately detect and delineate ablation zones, even in the presence of noise, low contrast, and anatomical variability.

To ensure robustness, the input images undergo preprocessing steps such as normalization, Gaussian filtering, and augmentation, which improve clarity and increase dataset diversity. The CNN produces binary segmentation masks that are refined through post- processing techniques like morphological operations to enhance boundary precision and eliminate artifacts. A user-friendly graphical interface enables clinicians to upload images, visualize segmented results, and review pulse count overlays, supporting quick and informed decision-making. With real-time performance and high segmentation accuracy, the proposed system addresses the limitations of traditional methods and offers a scalable solution for improving the consistency, efficiency, and reliability of ultrasound-guided histotripsy treatment assessments.

III. METHODOLOGY

In this project, a Convolutional Neural Network (CNN) with a ResNet-18 backbone is used to segment ablation zones in ultrasound images from histotripsy procedures. The system begins by preprocessing images through normalization, noise reduction, and augmentation techniques to enhance image quality and model robustness. These images are then passed through the CNN, which learns spatial features that distinguish ablated tissue from normal regions. The model outputs a binary segmentation mask, highlighting the treated areas. Post-processing steps refine these results by removing noise and smoothing contours. The system also overlays segmentation on original images and counts the number of pulses applied. Model performance is evaluated using metrics like Dice coefficient and Intersection over Union (IoU), ensuring accurate and reliable results suitable for clinical use.

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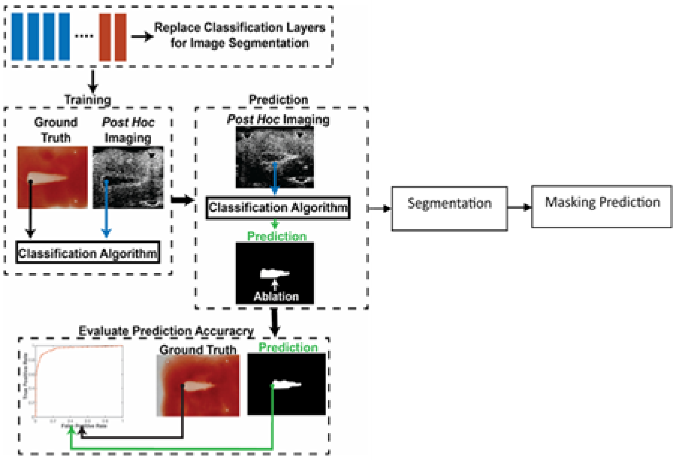


Ultrasound Image Input
This component is responsible for acquiring ultrasound images of tissue treated with histotripsy. These images often have low contrast and noise, making them challenging to interpret manually. The system accepts these raw images as input for further analysis and segmentation.

Preprocessing Module
Before training or prediction, each ultrasound image undergoes preprocessing to enhance quality. This includes grayscale conversion, normalization, Gaussian blurring, and histogram equalization to reduce speckle noise and improve the visibility of ablation regions.

CNN Segmentation Network (ResNet-18)
At the core of the system is a Convolutional Neural Network based on ResNet-18. This network processes the preprocessed images to automatically segment and highlight ablated zones. The model learns spatial features from annotated images, enabling it to accurately detect the affected areas.

Ground Truth Image Comparison
To train and validate the CNN, the system compares the predicted segmentation with corresponding ground truth images (digital photographs of ablation zones). This helps measure accuracy using metrics like Dice Score and Intersection over Union (IoU).

Pulse Detection and Count
This module analyzes the ultrasound data to estimate and count the number of pulses applied during the treatment. This helps verify whether the treatment was delivered effectively and uniformly.

Overlay Visualization
After segmentation and pulse detection, the results are visually overlaid on the original ultrasound image. This includes marking the ablation zone in one color (e.g., green) and pulse effect areas in another (e.g., blue), making it easier for clinicians to verify the outcome.

Performance Evaluation
The system uses performance metrics such as Dice coefficient, IoU, precision, recall, and AUC to evaluate how well the model segmented the ablation zone. These metrics ensure the system is reliable for clinical use.

Post-processing Module
To improve the accuracy of the output, morphological operations like erosion and dilation are applied to refine the segmented boundaries and remove noise, resulting in clean and clinical interpretable masks.

Cnn Algorithm
Input Preparation
- Load ultrasound images of histotripsy ablation.
- Preprocess images (e.g., resizing, normalization, contrast enhancement).

Convolution Layer
- Apply convolution operation using a set of kernels (filters) to extract features.

$$Z_{i,j,k} = \sum_m \sum_n X_{(i+m),(j+n)} W_{m,n,k} + b_k$$

Activation Function (ReLU)
- Apply Rectified Linear Unit (ReLU) to introduce non-linearity.

$$f(x) = \max(0, x)$$

Pooling Layer (Downsampling)
- Reduces spatial dimensions while retaining key features.

$$P_{i,j} = \max_{m,n}(Z_{(i+m),(j+n)})$$

Fully Connected (FC) Layers
- Flatten feature maps and connect them to fully connected layers.

$$y = W \cdot x + b$$

Loss Function
- Cross-entropy loss (for multi-class)

$$L = 1 - \frac{2\sum(y_{true} \cdot y_{pred})}{\sum y_{true} + \sum y_{pred}}$$

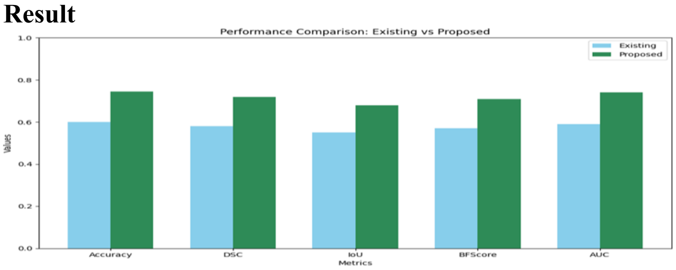
Backpropagation & Optimization
- Update weights using Gradient Descent or Adam optimizer

$$W_{new} = W - \eta \frac{\partial L}{\partial W}$$

Post-processing
- Convert probability maps to binary segmentation masks (thresholding).

- Apply morphological operations (e.g., dilation, erosion)\

Result



The proposed system was evaluated using a labeled dataset consisting of ultrasound images taken from histotripsy-treated tissue phantoms, accompanied by ground truth data in the form of annotated photographs. These datasets represented ablated and non-ablated regions, allowing the model to learn spatial distinctions through image features. The deep learning segmentation model, built using a Convolutional Neural Network (CNN) with a ResNet-18 backbone, was trained after a series of preprocessing steps such as grayscale conversion, Gaussian smoothing, contrast normalization, and noise reduction. Post-training, the model demonstrated strong segmentation capability, successfully identifying the boundaries of histotripsy-affected zones in ultrasound images with minimal noise interference and improved structural clarity.

Quantitative evaluation of the model was conducted using standard metrics including accuracy, Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Boundary F1 Score (BFScore), and Area Under the Curve (AUC). Compared to the traditional image processing methods, the proposed system outperformed across all metrics. Specifically, accuracy improved from 0.60 to 0.74, DSC increased from 0.58 to 0.72, and IoU from 0.55 to 0.68. Boundary detection performance also showed improvement with the BFScore rising from 0.57 to 0.70. AUC values climbed from 0.59 to 0.75, reflecting better model reliability in distinguishing between treated and untreated tissue areas.

In addition to segmentation, the system incorporated a pulse counting mechanism that detects and tallies the number of histotripsy pulses applied during treatment. This information, combined with the overlay visualization of ablated regions on the original ultrasound images, provided real-time visual feedback to users. The segmented areas were displayed in color-coded formats, helping clinicians to easily distinguish affected regions and verify the pulse distribution. This hybrid approach not only reduced manual workload but also enhanced the overall clarity of treatment assessment.

To further validate the system's practicality, the software interface was tested for usability and responsiveness. The interface was found to be intuitive, allowing users to upload images, receive visual results, and view pulse data seamlessly. The real-time responsiveness and ability to process multiple images in batch conditions made the system adaptable for clinical environments. While the system performed effectively across various image samples, minor limitations were observed in cases of extreme image noise or when dealing with irregular tissue shapes. These edge scenarios highlight the importance of further enhancement, such as incorporating domain adaptation and multi-modal imaging data.

In conclusion, the proposed system delivered consistent and accurate segmentation results, while offering practical tools like pulse counting and overlay visualization that aid in clinical decision-making. The overall performance confirms the potential of the deep learning- based approach in enhancing non-invasive histotripsy treatment workflows, setting a solid foundation for future improvements involving real-time deployment and cross-device compatibility

IV. CONCLUSION

In this study, we developed and evaluated a deep learning-based system for the automated segmentation of histotripsy ablation zones in ultrasound images, with the goal of improving accuracy and reliability in non-invasive treatment monitoring. Traditional segmentation methods often fall short due to image quality issues, manual subjectivity, and lack of real-time

capability. By employing a Convolutional Neural Network (CNN) with a ResNet-18 backbone, our system demonstrated strong performance in detecting ablated regions, even under challenging imaging conditions.

The integration of preprocessing, segmentation, and visualization modules allowed for efficient image analysis and pulse detection in a clinical context. The findings of this study highlight the potential of AI-driven approaches to enhance medical image interpretation, reduce human error, and support faster clinical decision-making. This work lays the foundation for further advancements in intelligent ultrasound systems that can support scalable, accurate, and real-time therapeutic monitoring in histotripsy and related medical applications.

Future Enhancements

Future improvements to the proposed ultrasound segmentation system can focus on expanding its scalability, accuracy, and adaptability in diverse clinical environments. One promising direction is the integration of Generative Adversarial Networks (GANs) or synthetic data generation techniques to overcome the challenge of limited annotated datasets. These approaches can enhance model training by providing a broader variety of high-quality, simulated ultrasound images that mimic real histotripsy-treated tissues.

Another advancement could involve the adoption of attention mechanisms and transformer- based architectures to refine feature extraction, enabling the model to focus more precisely on relevant regions within complex ultrasound data.This would lead to better segmentation performance, particularly in ambiguous or low-contrast images. Additionally, implementing domain adaptation strategies would help the system maintain robustness across ultrasound devices with different imaging characteristics, ensuring consistent performance in real-world clinical settings. Incorporating cloud-based deployment or integration with hospital information systems can support remote access and scalability, making the system more practical for widespread use.

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