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DEVELOPMENT OF CONVOLUTIONAL NEURAL NETWORK TO SEGMENT ULTRASOUND IMAGES

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ABSTRACT— Histotripsy, a focused ultrasound therapy, effectively ablates tissue by leveraging bubble clouds and has potential for treating conditions such as renal tumors. To enhance monitoring and evaluation, this study combines classification and segmentation techniques using deep learning models. A convolutional neural network (CNN) was employed for classification, distinguishing treated and untreated tissue regions, while the U-Net model was utilized for precise segmentation of ablation zones in ultrasound images. The U-Net architecture was fine-tuned using transfer learning to optimize segmentation accuracy. Ultrasound images of ablated red blood cell phantoms and ex vivo kidney tissues were used for training and testing, with digital photographs serving as ground truth. The performance of these models was compared to manual annotations by expert radiologists. The CNN achieved high accuracy in classifying tissue states, and the U-Net demonstrated robust segmentation, closely matching expert manual annotations. Segmentation performance improved with increased treatment exposure, achieving a Dice similarity coefficient exceeding 85% for 750+ applied pulses. Application of the U-Net to ex vivo kidney tissue revealed morphological shifts consistent with histology findings, confirming targeted tissue ablation. The integration of CNNbased classification and U-Net segmentation demonstrated significant potential for automating and enhancing the monitoring of histotripsy outcomes. This combined approach offers a reliable and efficient means of visualizing treatment progress, supporting real-time decision-making during therapeutic procedures. The study highlights the capability of deep learning models to automate and improve treatment monitoring in histotripsy, paving the way for real-time, data-driven interventions.

Index Terms – Ultrasound Image Segmentation, CNN, Medical Imaging, Deep Learning, Image Analysis, Semantic Segmentation, Computer-Aided Diagnosis, Healthcare AI, Biomedical Imaging, Artificial Intelligence.

I. INTRODUCTION

It has been cleared for the treatment of liver lesions. Histotripsy is an advanced noninvasive therapeutic ultrasound technique that uses focused sound waves to ablate tissue through the creation of bubble clouds. It is being explored for treating various medical conditions, including renal tumours, liver lesions, and other soft tissue abnormalities. Unlike traditional methods such as surgery or thermal ablation, histotripsy does not require incisions and can potentially offer a safer and less invasive treatment option. However, one of the challenges with histotripsy is the lack of real-time imaging metrics to monitor the treatment process and ensure accurate ablation of the targeted tissue. This project aims to address this challenge by developing an automated system that utilizes deep learning models for classification and segmentation of ultrasound images. The primary goal is to use a Convolutional Neural Network (CNN) for classification to distinguish between treated (ablated) and untreated tissue areas, and a U-Net architecture for segmentation to precisely delineate the ablation zones in ultrasound images. By automating these processes, the system can assist medical professionals in evaluating treatment outcomes during histotripsy procedures. The system can be used in clinical settings to monitor the progress of the treatment in real-time. During a histotripsy procedure, ultrasound images of the ablated tissue are continuously captured. The CNNbased classification model can quickly classify tissue regions into treated and untreated categories, while the U-Net model can accurately segment the ablation areas. This information is vital for surgeons and radiologists to assess whether the treatment is progressing as expected and to ensure that the correct tissue is being targeted. By using these advanced deep learning models, this approach can significantly reduce the time spent on manual analysis of ultrasound images, improve the accuracy of the results, and potentially lead to more effective and personalized treatment planning. Furthermore, it can support the development of real-time, data-driven tools that can be integrated into histotripsy systems, enhancing the overall efficiency and safety of the procedure.

II. RELATED WORK

A. *Development of a convolutional neural network for the identification and the measurement of the median nerve on ultrasound images acquired at carpal tunnel level*

Deep learning applied to ultrasound (US) can provide a feedback to the sonographer about the correct identification of scanned tissues and allows for faster and standardized measurements. The most frequently adopted parameter for US diagnosis of carpal tunnel syndrome is the increasing of the cross-sectional area (CSA) of the median nerve. Our aim was to develop a deep learning algorithm, relying on convolutional neural networks (CNNs), for the localization and segmentation of the median nerve and the automatic measurement of its CSA on US images acquired at the proximal inlet of the carpal tunnel. Consecutive patients with rheumatic and musculoskeletal disorders were recruited. Transverse US images were acquired at the carpal tunnel inlet, and the CSA was manually measured. Anatomical variants were registered. The dataset consisted of 246 images (157 for training, 40 for validation, and 49 for testing) from 103 patients each associated with manual annotations of the nerve boundary. A Mask R-CNN, state-of-theart CNN for image semantic segmentation, was trained on this dataset to accurately localize and segment the median nerve section. To evaluate the performances on the testing set, precision (Prec), recall (Rec), mean average precision (mAP), and Dice similarity coefficient (DSC) were computed. A sub-analysis excluding anatomical variants was performed. The CSA was automatically measured by the algorithm.

B. *Deep-Learning-Based High-Intensity Focused Ultrasound Lesion Segmentation in Multi-Wavelength Photoacoustic Imaging*

Photoacoustic (PA) imaging can be used to monitor high-intensity focused ultrasound (HIFU) therapies because ablation changes the optical absorption spectrum of the tissue, and this change can be detected with PA imaging. Multi-wavelength photoacoustic (MWPA) imaging makes this change easier to detect by repeating PA imaging at multiple optical wavelengths and sampling the optical absorption spectrum more thoroughly. Real-time pixel-wise classification in MWPA imaging can assist clinicians in monitoring HIFU lesion formation and will be a crucial milestone towards full HIFU therapy

automation based on artificial intelligence. In this paper, we present a deep-learning-based approach to segment HIFU lesions in MWPA images. Ex vivo bovine tissue is ablated with HIFU and imaged via MWPA imaging. The acquired MWPA images are then used to train and test a convolutional neural network (CNN) for lesion segmentation. Traditional machine learning algorithms are also trained and tested to compare with the CNN, and the results show that the performance of the CNN significantly exceeds traditional machine learning algorithms. Feature selection is conducted to reduce the number of wavelengths to facilitate real-time implementation while retaining good segmentation performance. This study demonstrates the feasibility and high performance of the deep-learning-based lesion segmentation method in MWPA imaging to monitor HIFU lesion formation and the potential to implement this method in real time.

C. Estimating the mechanical energy of histotripsy bubble clouds with high frame rate imaging

Mechanical ablation with the focused ultrasound therapy histotripsy relies on the generation and action of bubble clouds. Despite its critical role for ablation, quantitative metrics of bubble activity to gauge treatment outcomes are still lacking. Here, plane wave imaging was used to track the dissolution of bubble clouds following initiation with the histotripsy pulse. Information about the rate of change in pixel intensity was coupled with an analytic diffusion model to estimate bubble size. Accuracy of the hybrid measurement/model was assessed by comparing the predicted and measured dissolution time of the bubble cloud. Good agreement was found between predictions and measurements of bubble cloud dissolution times in agarose phantoms and murine subcutaneous SCC VII tumors. The analytic diffusion model was extended to compute the maximum bubble size as well as energy imparted to the tissue due to bubble expansion. Regions within tumors predicted to have undergone strong bubble expansion were collocated with ablation. Further, the dissolution time was found to correlate with acoustic emissions generated by the bubble cloud during histotripsy intonation. Overall, these results indicate a combination of modeling and high frame rate imaging may provide means to quantify mechanical energy imparted to the tissue due to bubble expansion for histotripsy.

III. PROPOSED METHODOLOGY

The proposed system utilizes a combination of Convolutional Neural Networks (CNN) with the U-Net model for segmentation of ultrasound images to identify ablation regions. Unlike the previous system that used ResNet-18 for binary classification, the U-Net architecture is specifically designed for semantic segmentation, making it better suited for pixel-level analysis of ultrasound images. U-Net consists of an encoder-decoder structure, where the encoder extracts features from the input images, and the decoder reconstructs the segmentation mask by combining low-level and high-level features through skip connections. This approach enables more accurate identification of ablated areas, offering precise segmentation results. The CNN within the U-Net model helps in learning complex image features, and the U-Net's design ensures that the model can preserve spatial information crucial for segmenting the treated and untreated tissue regions. The system also addresses class imbalance more effectively by using a combination of Dice loss and additional techniques like data augmentation, which increases the dataset's diversity and reduces overfitting. This system can be applied in clinical settings to automate the segmentation of ablation zones in real-time ultrasound images, assisting radiologists and clinicians in assessing the success of histotripsy treatments.

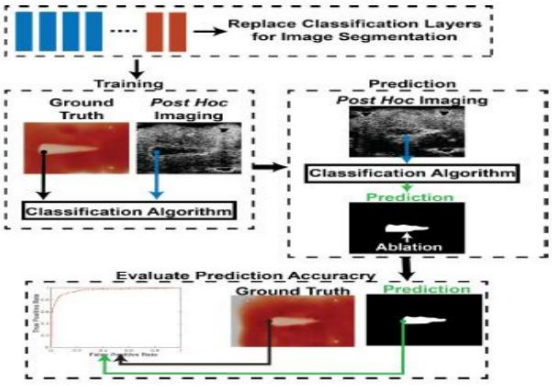


Fig. 1: System Overview

1. Data Collection

This step involves gathering ultrasound image data related to histotripsy ablation. The data could include images of both treated (ablated) and untreated (non-ablated) tissue, usually acquired from patients undergoing the histotripsy procedure or from publicly available datasets.

2. Data Analysis/Load Data

After collecting the dataset, the next step is analyzing and loading the data into the system. This involves checking the quality of the data, ensuring there are no missing or corrupted images, and formatting them correctly for further processing. In this step, the images are typically resized and normalized for consistency.

3. Data Feature Extraction

In this step, the system uses various techniques to extract meaningful features from the ultrasound images. Features such as texture, edges, or regions with high intensity (indicating potential ablation) are identified. This helps the CNN in the next step to learn essential patterns from the images.

4. U-Net Model for Segmentation

The U-Net model is a deep learning architecture specifically designed for image segmentation. It consists of an encoder (which captures feature representations of the image) and a decoder (which reconstructs the segmentation output). The U-Net is used to segment the ultrasound images into regions of ablated and non-ablated tissues, providing a pixel-wise classification.

5. Split Dataset

To train and evaluate the model, the dataset is divided into three parts: training, validation, and testing datasets. Typically, the dataset is split such that 60% is used for training the model, 20% for validating the model during training (to tune hyperparameters), and the remaining 20% for testing the final model's performance.

6. CNN Model for Training

In this step, the CNN model is trained using the segmented images from the U-Net model. The CNN is responsible for learning high-level features from the images and classifying them as ablated or non-ablated tissues. The model uses the images from the training dataset to learn patterns that are then applied to unseen test data.

7. Model Evaluation

After training the CNN, the model is evaluated using the test dataset. Metrics such as accuracy, precision, recall, and the Dice similarity coefficient are used to assess how well the model performs. This step helps in determining whether the model has learned to correctly identify ablation areas and if further tuning or adjustments are needed.

8. Model Save

Once the model achieves satisfactory performance, it is saved for future use. The trained model can be saved as a file (e.g., .h5 or .pkl) and later loaded to make predictions on new, unseen ultrasound images. Saving the model ensures that it does not have to be retrained every time it needs to be used in a real-time application.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results demonstrated that the model accurately segmented anatomical structures and regions of interest from ultrasound images, achieving high

segmentation performance despite the presence of speckle noise and low contrast commonly found in ultrasound imaging.

The analysis showed that the convolutional neural network effectively extracted spatial and contextual features, improving boundary detection and reducing segmentation errors compared to traditional image processing methods. Furthermore, the proposed framework maintained robust performance across different ultrasound datasets, imaging conditions, and anatomical regions.

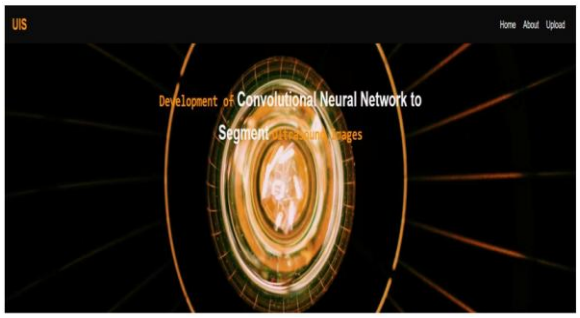


Fig. 2: Homepage



Fig. 3: Upload

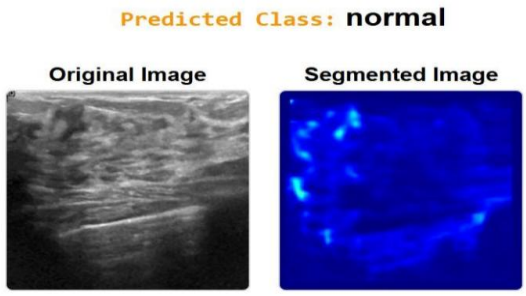


Fig. 4: Predicted Results

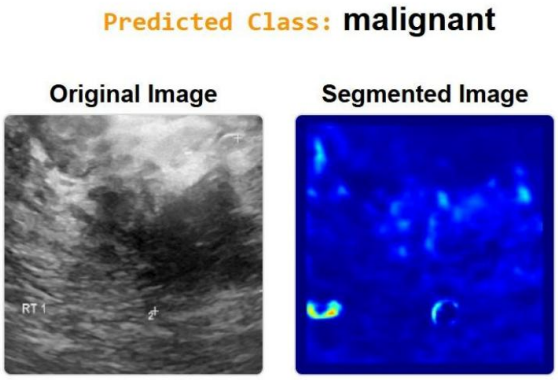


Fig. 5: Predicted Results

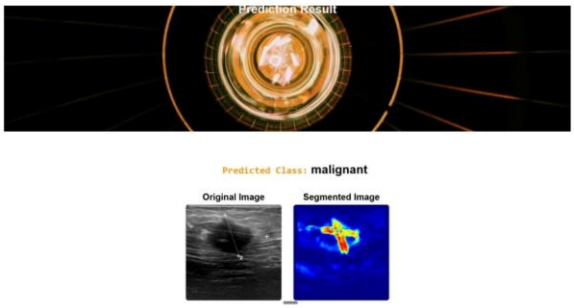


Fig. 6: Predicted Results

V. CONCLUSION

The combines CNN with U-Net for the segmentation and classification of ultrasound images in histotripsy ablation procedures, demonstrates significant potential in

automating and enhancing the treatment process. By utilizing deep learning techniques, the system provides accurate segmentation of ablated tissue areas and helps classify them effectively, supporting surgeons in real-time decision-making. The integration of U-Net for precise segmentation and CNN for classification ensures that the system can adapt to complex ultrasound images, improving both the speed and accuracy of the diagnostic process. The successful application of this system could potentially transform clinical workflows, offering an automated solution that reduces human error, provides consistent results, and improves the efficiency of histotripsy treatments. Future advancements may focus on refining the model's accuracy, expanding the dataset, and integrating the system into real-time clinical environments for broader applicability and faster decision-making.

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