

## Article

# Towards Automating Junctional Hemorrhage Control Using AI for Interpretation of Human Tissue

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## Abstract

Junctional hemorrhage has a high fatality rate due to how difficult it is to control rapid bleeding from major vessels. The available methods to stop junctional blood loss are prone to placement errors as well as failure during transport and during prolonged field care. On the battlefield, medical imaging with a portable ultrasound can be leveraged for visualization of the underlying tissue and application of compression at the anatomical junction to effectively stop blood flow. In this work, we developed AI models for anatomical landmark tracking using a perfused human cadaver model. These AI models were paired with an end-user clinical application to guide proper placement and compression, improving junctional hemorrhage control on the future battlefield. The trained U-Net semantic segmentation model demonstrated strong performance across predictions for both validation and hold-out, blind subjects. Overall pixel accuracy across the dataset was 98.9% for training and 98.6% for blind subjects. The artery and vein predictions achieved the highest class-specific training intersection-over-union scores, both at 0.73. This segmentation model trained to interpret human tissue provides evidence that ultrasound visualization can help guide compression at anatomical junctions. Future work will focus on improving blind performance for implementation of this AI model into closed-loop control of hardware prototypes, delivering real-time predictions and control.

**Keywords:** ultrasound; segmentation; artificial intelligence; hemorrhage control; automation



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## 1. Introduction

Junctional hemorrhage control continues to be a major challenge in trauma situations due to rapid bleeding from major vessels and limited effective resources to promptly stop blood loss [1,2]. In contrast to extremity hemorrhage, where the widespread prehospital use of circumferential tourniquets has had a positive effect on mortality reduction, these tools are not applicable to anatomical junctions such as the groin, axilla, or neck [3–5]. In these regions, the current standard of care for hemorrhage control is limited to manual application of pressure, wound packing, and specialized tourniquets that are tailored for the anatomy [6,7]. These methods, however, are prone to failure due to improper placement, slippage during transport, operator fatigue, and risk of re-bleed, all of which are more prevalent in austere environments where prolonged care may be required prior to definitive medical care [4,8–10].

To improve the efficacy of prolonged occlusion at anatomical junctions, recent research has explored the possibility of using ultrasound technology for tissue compression [10]. By utilizing an ultrasound transducer as the device with which to compress the vessel, the medical provider can visualize the underlying anatomy, ensuring alignment of the vessels with a hard, osseous surface to effectively occlude flow [11]. The precise alignment can readily be achieved and recognized by a skilled and experienced sonographer, but this skill-level may not be readily available at the point of injury, where hemorrhage control is most critical. For instance, a user inexperienced in ultrasound interpretation may need to manage hemorrhage control in a remote or battlefield environment. In these situations, there is a need for automated analysis of the ultrasound scan to readily guide intervention and provide clinical decision support [12,13].

For medical image interpretation, artificial intelligence (AI) has become a widely used approach that can provide assistance by highlighting anatomical structures [14,15]. AI for ultrasound image interpretation can take many implementations from classification models to identify injury states, object detection models that can provide bounding boxes over regions of interest, and segmentation models that provide pixel level detailed labels. Image classification models have been used in ultrasound imaging applications for malignant tumor classification [16], obstetric applications [17], and point-of-care ultrasound triage applications [18]. However, image classification does not provide spatial information within the ultrasound image about where features are present, making them less useful for guiding a user to the proper occlusion site. Object detection has been used for tracking lesions [19], fetal properties [20], and guiding needle placement for various applications [21,22]. While object detection provides location and approximate geometrical properties, the bounding boxes cannot accurately track irregular object shapes or angles accurately.

As such, for this hemorrhage control application, image semantic segmentation provides a superior level of interpretability, by delivering a pixel-by-pixel description of the anatomy in view. Segmentation models can make use of fully convolutional networks (FCNs), encoder-decoder architectures, transformer-based models, or even foundational model types [23]. FCN models mark the initial semantic segmentation models, wherein convolutional output layers export spatial pixel-level maps [24,25]. These models have been used for tracking colorectal [26] or brain [27] tumors from MRI images and catheter segmentation from ultrasound images [28]. FCNs often have low resolution outputs and are less widely used for medical imaging applications. Encoder-decoder architectures use a contracting path (encoder) to identify image features and an expanding path (decoder) to provide precise feature location. These model types are widely used for medical imaging applications, with U-Net being the most well-known architecture [29] that continues to be widely used for various applications such as classifying stroke risk based on plaque build-up [30], guiding vascular robotic interventions [31], and assessing proximity of shrapnel to anatomical structures [32]. U-Net is lightweight but is built on convolutional models that struggle to track global feature relationships [33]. U-Net++ was proposed to introduce additional dense short-range connections to improve feature tracking [34]. Furthermore, U-Net has been modified with transformer and attention mechanisms to better track global trends across images [35]. For example, TransUNet [36,37] has been used for tracking brain tumors [38], and Swin-UNet [39] has been used for medical device placement tracking within the Inferior Vena Cava [40]. Each of these improvements suffers from similar challenges, primarily that larger datasets are required to properly train these models. The final segmentation model type is foundational models pre-trained on large diverse image datasets, allowing for zero-shot learning of new applications through interactive model training [33]. The most common foundation model is Meta's segment anything model (SAM) that is built with an encoder-decoder and transformer architecture with a 1 billion

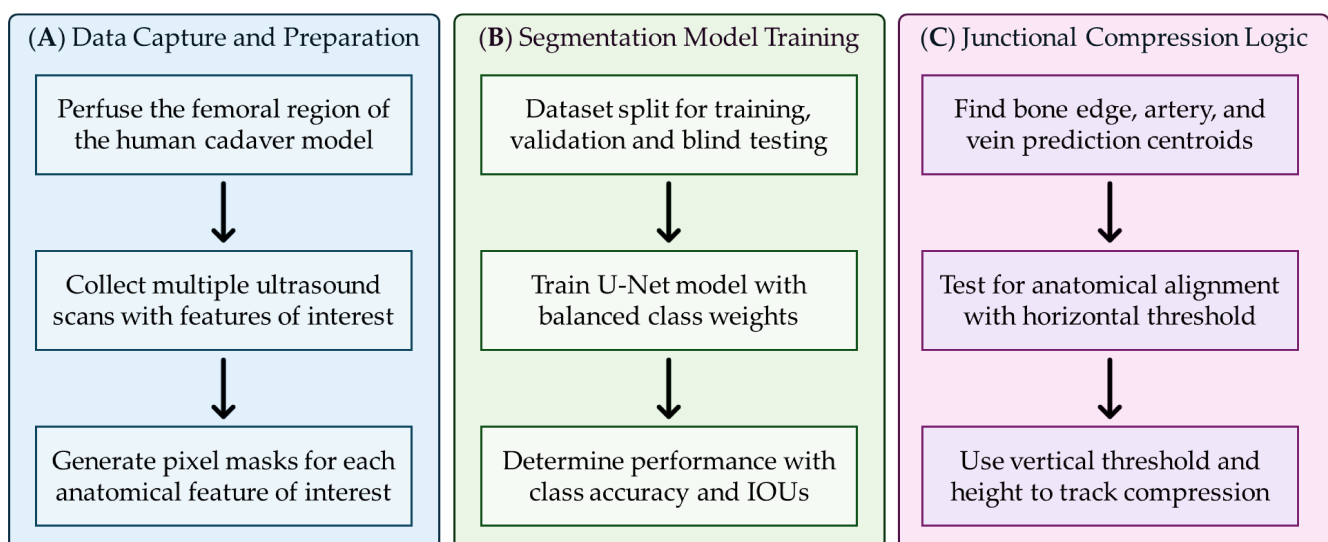
mask dataset [41]. While a promising advancement, SAM is heavily biased by its prompt and higher order transfer learning is needed to achieve clinical accuracies as described in other recent studies [33].

A segmentation mask delineating the features of interest generated by an AI model is ideal for guiding junctional hemorrhage control and further implementation within novel tourniquet designs. The segmentation AI model can provide both dynamic guidance to the correct anatomical location and then assessment of vessel compression to achieve occlusion. For initial application of these models with limited datasets U-Net was selected, for proof-of-concept, as it is widely used and less data intensive compared to other semantic segmentation model types.

Previous work has shown how paired AI models can track occlusion [42] and be integrated with hardware prototypes [43] as a prototype for ultrasound-based junctional tourniquets. However, these studies utilized tissue-mimicking phantoms which have limited anatomical complexity and subject variability compared to human tissue, lessening the translation-level for these technologies. Further, these prior studies used a combination of classification and object detection AI models instead of a single segmentation model. Here, we show how a sole segmentation AI model can be used to track anatomical features and vessel compression in the femoral region of a perfused human cadaver. We hypothesize that a segmentation model trained on high-fidelity human anatomical data can robustly identify the artery, vein, and underlying osseous landmarks with sufficient accuracy to guide automated compression. By establishing the visual interpretation of the automated system, this work lays the foundational logic required for a closed-loop, robotic junctional tourniquet capable of functioning autonomously in pre-hospital trauma environments.

## 2. Materials and Methods

The work described in this article encompasses data capture from a perfused human cadaver model to an AI-guidance application to track junctional compression as summarized in the flow diagram on Figure 1 and detailed in the subsequent sections.



**Figure 1.** Flow diagram of methods to develop a segmentation model to guide junctional compression. Overall steps taken are detailed for each stage of the work: (A) data capture and preparation, (B) segmentation model training, and (C) junctional compression logic application development.

### 2.1. Perfused Human Cadaver Model

A human research determination was submitted along with a request for OHARO approval for regulatory oversight of image capture in the human cadaver model. Once

all approvals were obtained, prospective ultrasound data was collected from recently deceased, consented, serologically screened (negative), fresh (never frozen), unembalmed, human specimens without external evidence of previous vascular surgery or injury to the femoral area.

The perfused cadaver model was set up with both arterial and venous flow. For arterial access, a 4–5 cm longitudinal incision was created medial to the femur, within the adductor canal, to gain access and appreciate the femoral artery. Visualization of the artery was accomplished with blunt dissection, isolation, and subsequent elevation. Following elevation, a finder needle and guidewire (Teleflex, Wayne, PA, USA) were inserted cephalad, using the Seldinger technique, followed by dilation and placement of a Triple-Lumen Central Venous Catheter (Teleflex, Wayne, PA, USA). The arterial catheter was then sutured into position where, once secured, the catheter was connected to a LifeFlow (410 Medical, Durham, NC, USA) rapid infusion syringe pump system to generate manual pulsatile arterial flow. Ultrasound color flow and Doppler were then utilized to confirm catheter placement and dynamic flow in the femoral junction region.

For venous access, a 2 cm vertical incision was made anterior to the medial malleolus, offering visual appreciation and access to the greater saphenous vein. The vein was then isolated with blunt dissection and elevated. Following elevation, a finder needle and guidewire (Teleflex, Wayne, PA, USA) were inserted cephalad, followed by placement of a 7 Fr Cordis Introducer Sheath (Teleflex, Wayne, PA, USA). The sheath was then sutured into position and connected to a LifeFlow (410 Medical, Durham, NC, USA) rapid infusion syringe pump system to manually generate steady venous flow. Ultrasound color flow was also used to confirm catheter placement and dynamic flow in the region of interest.

## 2.2. Ultrasound Data Capture

All ultrasound scans were captured with a portable ultrasound system (L7 HD3 Linear Scanner, Clarius, Vancouver, BC, Canada) at the femoral junction region as three 10 s clips for various motions around the inguinal crease. For each motion, the scan capture started with the major artery and vein aligned with the bone. These motions included a lateral swipe, a vertical sweep, cranial to caudal tilting, lateral rocking, light compressions, and full compressions. During the light compression motion, the femoral junctional area was lightly compressed approximately three times within each clip duration, wherein the vein collapsed under pressure but the artery maintained patency. In contrast, during the full compression clips which attempted to achieve complete flow stop using the ultrasound transducer to apply pressure, fully collapsing both vessels against the underlying osseous surface. Occlusion was confirmed with a secondary ultrasound in the abdomen, downstream of the direction of fluid flow in the perfused human cadaver model.

## 2.3. Dataset Preparation

All data processing and scripts were performed and written using MATLAB. To prepare the data for curation, the ultrasound scans for each motion were merged into a 30 s video and downsampled to every 5th frame to streamline the data annotation process. The processed videos were imported into MATLAB video labeler (2024b, Mathworks, Natick, MA, USA) application along with the label definitions template. The definitions included pixel labels for: (i) major artery, (ii) major vein, (iii) any vessel branches, (iv) bone edge, (v) where the ultrasound probe had no contact with the skin, and for the compressed (vi) artery and (vii) vein. These last two labels were reserved for when the secondary ultrasound had confirmed flow stop for the full compression motion scans. Once datasets were fully annotated, all labels were verified before further processing. A script was written to process the downsampled video and extract frames to match each frame with an existing

pixel label, generating a directory of matching frames and pixel label data ready for use in AI model training. Added functionality allowed to generate the directory specifying what classes to include.

#### 2.4. Segmentation Model Development

A semantic segmentation U-Net architecture was trained to generate prediction masks for multiple classes [44]. Approximately 15% of the dataset, or 3 complete subjects, were separated from training as a blind holdout group. For the remaining subjects, the dataset was split 85:15 training to validation from the total remaining images and paired to their respective pixel label masks before resizing both to  $512 \times 512$  pixels. A detailed breakdown of total images by use, yields: 12,009 images for training, 2119 images for validation, and 2519 images for testing; all testing images were from three independent subjects while training and validation images were both from the other 19. All training was performed using MATLAB (v. R2024b, Mathworks, Natick, MA, USA) on a computer with Windows 11 Pro operating system, Intel Xeon Gold processor and a PNY NVIDIA RTX A6000 graphics card with 48 GB of video RAM. The U-Net architecture was 4 layers deep with 64 encoder filters, and had a total of 31 M trainable parameters. Training used the Adaptive Moment Estimation (adam) [45] as the architecture optimizer, with an initial learning rate of  $1 \times 10^{-3}$  using a piecewise schedule to reduce the rate by a factor of 10 every 10 training epochs. To improve model generalizability, data was shuffled prior to every epoch, and training was allowed up to a maximum of 100 epochs with a validation patience of 5 epochs set as an early stop criterion, which would halt training if validation accuracy did not improve for five consecutive epochs. Validation was performed every 371 iterations to ensure at least one validation check per epoch and using a batch size of 32. In addition, some model iterations were trained with an added U-Net pixel classification layer to account for class imbalance, using the median frequency of each pixel to balance class weights [46] which utilizes a weighted cross-entropy loss function. The hyperparameters used during model training were selected based on previous experience using U-Net for interpretation of ultrasound images [32], and modified based on available computational power.

#### 2.5. Model Performance Evaluation

The predictive performance of trained segmentation models was assessed on both the validation data and the blind holdout data described above. Model predictions were compared against the corresponding ground truth pixel masks for each anatomical class and the overall video frame. True positive, true negative, false positive and false negative classifications were determined at a pixel level and were analyzed globally and for each class of the testing dataset. The target pixel accuracy goal for blind predictions was set at 85%, evaluating the models' overall capability to differentiate the anatomical features of interest from the background. Recognizing that these features of interest are a small percentage of the total image, a secondary metric intersection-over-union (IOU) was used to evaluate the spatial overlap between the prediction and the ground truth mask. The target IOU threshold was set at 0.5.

#### 2.6. Clinical Logic for Junctional Compression

For evaluating the clinical application of the AI model, an algorithm was written to retrospectively process videos and determine if anatomical vessel features were aligned with the bone edge, followed by tracking vessel compression. To do this, the trained segmentation model was used to generate prediction masks for all the blind subject videos. Then, resulting predictions for the bone edges, arteries and veins were processed to measure the centroid of each prediction and its height. With this information, a series of logic gates were used to determine proper anatomical alignment of the vessels and underlying bone.

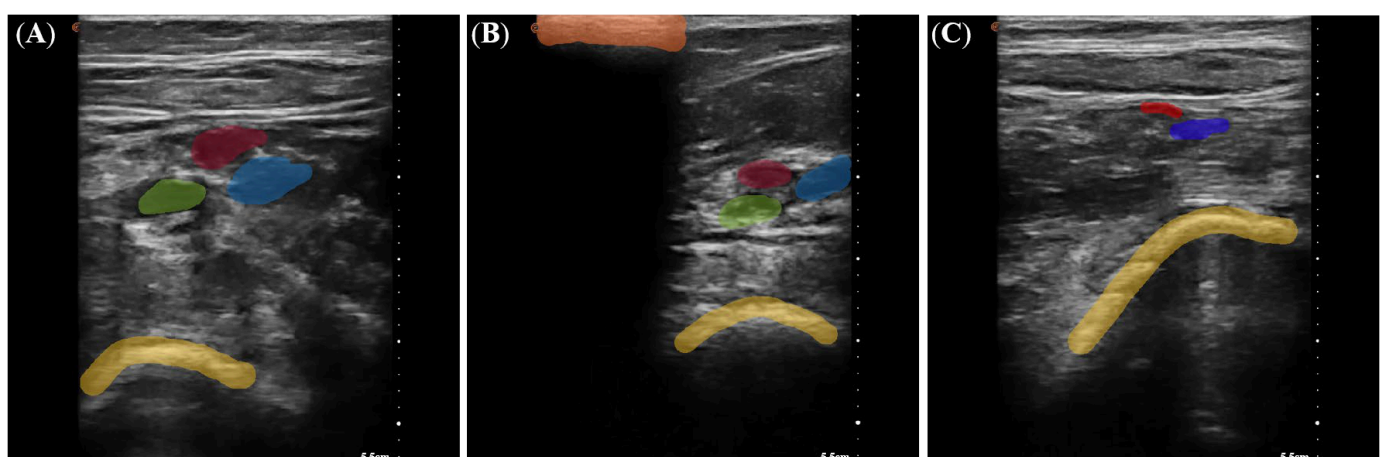
The first logic step determined whether the bone was centered in the frame, defined as threshold within the central, horizontal 40% of the image. If not, instructions would be displayed to slide the probe left or right, depending on where the bone prediction was identified. When no bone prediction was found, the display would instruct to reposition probe at or near the inguinal crease.

Once the bone was aligned in the center, the script assessed for any vessel prediction, artery or vein, to test for anatomy alignment. If the vessels were found, the script would trigger compression; otherwise, it would suggest fanning the probe while keeping the bone centered to potentially detect any vessels. Finally, when both criteria were met, and compression initiation triggered, the algorithm would keep track of the vertical distance traveled by the bone prediction and the height of the vessel prediction(s), which should decrease during effective compression. If the bone reached a vertical threshold in the image, the compression was considered successful. If at any point the bone traveled to its original position or the height of the vessel prediction increased, then the compression action ended. Retrospective ultrasound scans for several subjects were analyzed through the compression algorithm to evaluate the functionality of the developed logic.

### 3. Results

#### 3.1. Dataset Description

Ultrasound scans were captured in 23 re-perfused human cadavers of which 22 datasets were annotated after curation; one subject was excluded from data annotation and further use due to poor visibility of the anatomical features of interest in the captured ultrasound scans. The average age of the population was 77 years, and there was a near equal split between female and male subjects. In total, 16,647 frames were labeled across the six motions capture including seven classes: major artery, major vein, vessel branches (as a single label), bone edge, no contact from ultrasound probe (at the top of the image), compressed artery, and compressed vein, where appropriate. As expected, the overwhelming majority of pixels in the dataset pertained to the background at 97.1%. Excluding the background, the bone edge was the most prevalent category at 32.5% of labeled, non-background pixels, followed by vein at 27.8%. A summary table of pixel distribution by class labeled is included in Table 1. Example labels for all classes are shown in Figure 2 from different motions.



**Figure 2.** Representative annotated frames. Frames from the rocking (A,B) and full compression (C) motions are shown to illustrate the various classes labeled. In yellow is the bone edge, lighter red for the artery, lighter blue for the vein, green for the vessel branch, orange for areas where ultrasound probe had no contact, darker red for compressed artery, and darker blue for compressed vein. Depth of ultrasound imaging for the shown frames was enhanced in each image for clarity.

**Table 1.** Pixel distribution by class. Summary of pixel counts and percentages including or excluding background to highlight the pixel distribution for each annotated class.

| <i>Class</i>             | <i>Pixel Count</i> | <i>Pixel Percentage,<br/>With Background</i> | <i>Pixel Percentage,<br/>No Background</i> |
|--------------------------|--------------------|----------------------------------------------|--------------------------------------------|
| <i>Artery</i>            | $3.97 \times 10^7$ | 0.523%                                       | 18.042%                                    |
| <i>Vein</i>              | $6.10 \times 10^7$ | 0.804%                                       | 27.721%                                    |
| <i>Vessel Branch</i>     | $4.14 \times 10^7$ | 0.545%                                       | 18.814%                                    |
| <i>Bone Edge</i>         | $7.16 \times 10^7$ | 0.943%                                       | 32.538%                                    |
| <i>No Probe Contact</i>  | $4.58 \times 10^6$ | 0.060%                                       | 2.081%                                     |
| <i>Compressed Artery</i> | $9.31 \times 10^5$ | 0.012%                                       | 0.423%                                     |
| <i>Compressed Vein</i>   | $8.37 \times 10^5$ | 0.011%                                       | 0.380%                                     |
| <i>Background</i>        | $7.37 \times 10^9$ | 97.101%                                      |                                            |

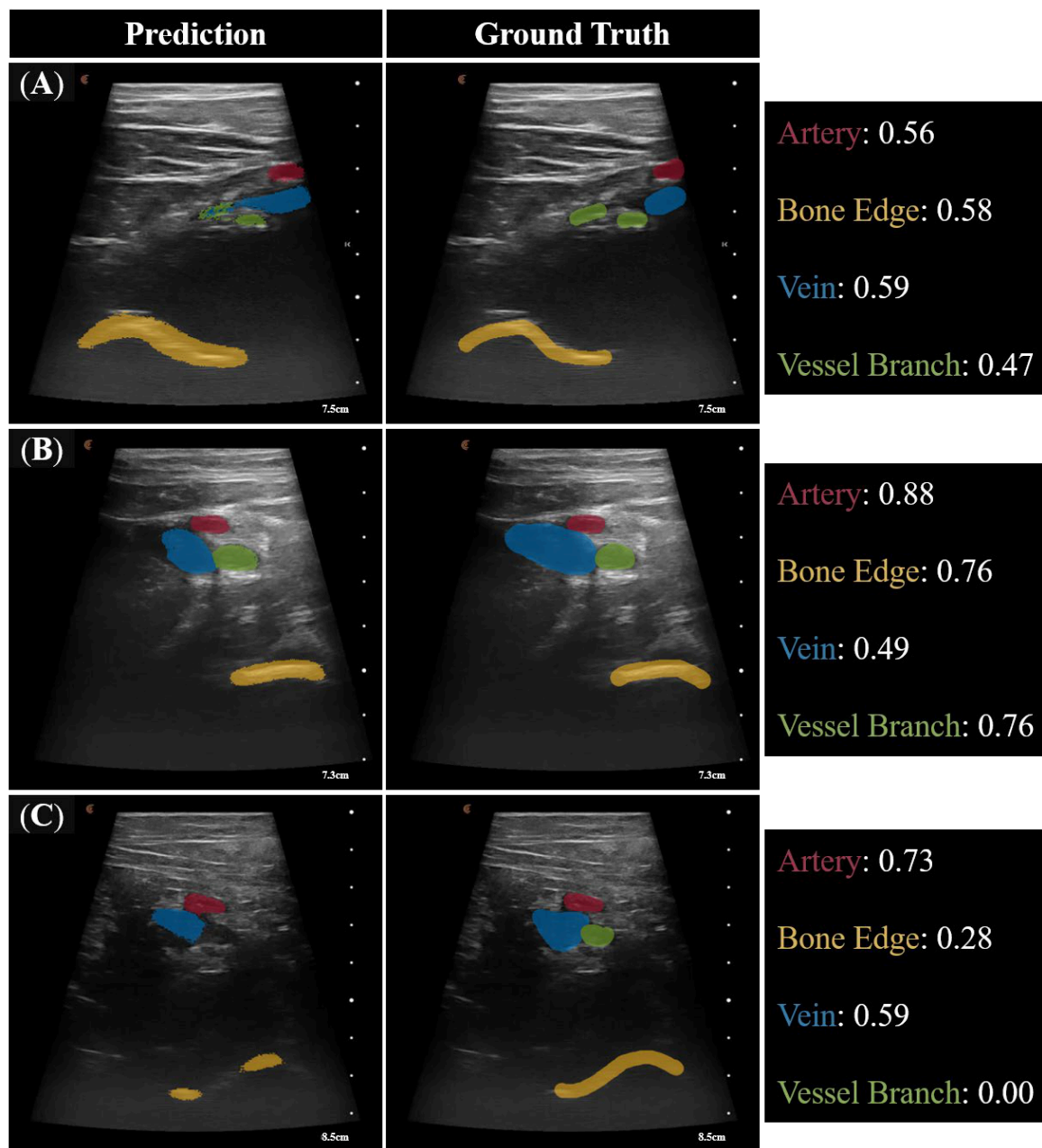
### 3.2. Segmentation Model Performance

The U-Net model demonstrated strong performance across predictions for both validation and the hold-out subjects. Overall pixel accuracy across the dataset was 98.9% for training and 98.6% for blind subjects. Global metrics were noticeably higher than class-specific performance for both training and blind datasets. Acknowledging the role of the background class in these metrics, class-specific scores are reported in Table 2. The artery and vein predictions achieved the highest training class-specific IOU scores, both at 0.73, with a noticeable decline for the blind subjects at 0.41 and 0.31, respectively. The classes with the worst accuracy and IOU scores were compressed artery and compressed vein with training accuracies of 32.5% and 3.6% as well as IOUs of 0.26 and 0.03, respectively. These values show a large difference from the overall training and blind metrics which were skewed by the background class, i.e., the IOU score for the overall data set was 0.98 for both training and blind subjects.

**Table 2.** Segmentation model performance metrics. Summary of accuracy and IOU scores for the global dataset and each class for training and blind hold-out datasets.

| <i>Class</i>                | <i>Training Accuracy</i> | <i>Training IOU Scores</i> | <i>Blind Accuracy</i> | <i>Blind IOU Scores</i> |
|-----------------------------|--------------------------|----------------------------|-----------------------|-------------------------|
| <i>Background</i>           | 99.5%                    | 0.99                       | 99.6%                 | 0.99                    |
| <i>Artery</i>               | 84.0%                    | 0.73                       | 48.1%                 | 0.41                    |
| <i>Vein</i>                 | 81.8%                    | 0.73                       | 38.6%                 | 0.31                    |
| <i>Vessel Branch</i>        | 62.5%                    | 0.55                       | 11.5%                 | 0.10                    |
| <i>Bone Edge</i>            | 76.9%                    | 0.63                       | 72.3%                 | 0.54                    |
| <i>No Contact (Probe)</i>   | 84.5%                    | 0.69                       | 34.0%                 | 0.29                    |
| <i>Compressed Artery</i>    | 32.5%                    | 0.26                       | 0.64%                 | 0.00                    |
| <i>Compressed Vein</i>      | 3.6%                     | 0.03                       | 0.05%                 | 0.00                    |
| <i>Global Pixel Metrics</i> | 98.9%                    | 0.98                       | 98.6%                 | 0.98                    |

For the functional application of the segmentation AI model the classes of focus were artery, vein, and bone edge, since these were the main drivers of the compression and alignment logic. Among these classes, the Bone edge was the only class to supersede a 0.5 IOU score for blind predictions, achieving 0.54. Although the blind IOU scores for the other classes are below 0.5, qualitative assessment of the predictions showed general tracking of the relevant features (Figure 3).

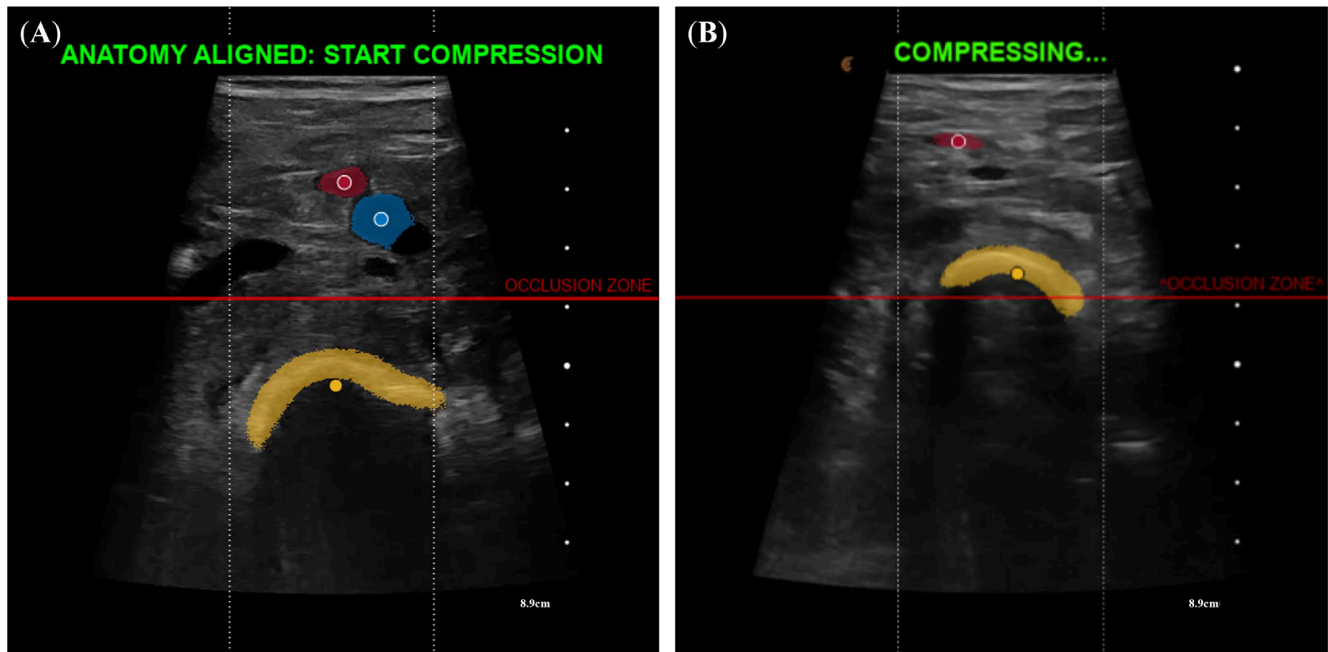


**Figure 3.** Predicted anatomical features for a blind subject. Shown are representative predictions for the blind subjects with predicted mask (left) and ground truth mask (right) along with IOU scores for each predicted class for frames with: (A) IOUs around 0.5, (B) above average IOUs for all classes, and (C) a missed vessel branch and below average bone prediction. Depth of ultrasound imaging for the shown frames was enhanced in each image for clarity.

### 3.3. Junctional Compression Guidance Application

To translate the predicted segmentation masks into actionable guidance for junctional compression, the center and boundaries of the anatomical features were extracted from the predictions. Testing at this stage was constrained to the lateral swipe, light compression and full compression motions for proof-of-concept evaluation of the guidance logic. The post-processing algorithm successfully calculated the center of the bone, artery and vein predictions, across the retrospectively tested videos. The average error of the centroid of each class for the blind subject predictions was 15.33, 18.36, and 11.58 pixels for each class, respectively. For purposes of this evaluation, both artery classes (compressed and normal) were merged, as well as both vein classes. A functional display of the video analysis

shows the horizontal bounds of the bone prediction to be qualified as in the center of the image (Figure 4A). Text in the top of the video playback displays if the bone is centered or if the ultrasound probe needs to slide left or right (Figure 4). Another horizontal line represented the threshold distance for vertical travel of the bone edge prediction when performing compression.



**Figure 4.** Representative visual output of the compression guidance. In the display output, (A) the user is shown a horizontal center threshold (white dotted lines) to consider the anatomy aligned and thus inform the user to begin compression. (B) An occlusion zone vertical threshold (in red) monitors compression. For the images shown, the predicted masks for the artery are in red, vein in blue, and bone in yellow. Depth of ultrasound imaging for the shown frames was enhanced in each image for clarity.

#### 4. Discussion

The continuity of hemorrhage as a leading cause of death following trauma requires innovative solutions to help stop the bleed at the point of injury [47]. Junctional hemorrhage is known to be particularly difficult to control, which is why a smart, adaptive intervention can greatly reduce the burden of care for these types of complex injuries. The utilization of ultrasound for aiding this technical gap leverages an already well-known, portable medical imaging technology, integrated with automated interpretation AI models [48]. This provides the end-user visualization during positioning and occlusion, as well as continuous monitoring if prolonged use is required.

The primary finding of this work is that a semantic segmentation model can accurately identify key anatomical structures for guiding femoral compression using a portable ultrasound system. This work specifically evaluated performance of a segmentation model instead of classification or object detection because of the ease-of-interpretation provided by delineation of anatomical landmarks. A classification model would only provide an overall assessment of the entire image returning a categorical output without any visualization. An object detection model does provide a bounding box around each object of interest found but lacks the detail of a pixel-by-pixel prediction mask. This additional level of detail is key when the AI model has two very important tasks: identifying and aligning anatomical landmarks to then analyze vessel patency to track compression.

The trained U-Net model achieved and surpassed the threshold performance metrics for the training dataset; however, this was not true for the blind dataset. The lower IOU scores for the blind prediction indicate that the model did not have enough training data to generalize predictions for the various features. A larger training dataset would provide more robust model training, and introduce sufficient biological variability to improve blind performance, which will be pursued in future work. However, the trained model was able to achieve the expected performance metrics thresholds within the training dataset. Despite the lower blind performance metrics, the AI model predictions could demonstrate the compression guidance logic was able to identify the three classes of interest, determine alignment, and trigger compression. This is likely due to the bone being the primary driver of anatomical alignment and compression tracking, with an IOU score of 0.54. As a proof-of-concept, these results show that a segmentation model can be used for both tasks, as opposed to having to swap between AI models for anatomical feature detection and then for tracking compression. This methodology can be successfully implemented when the final task of the second model is a diagnostic decision that would not require hardware control [49]. For this initial study, we only focused on a single U-Net model architecture which may not be optimal for this application. A wide range of semantic segmentation models have been developed, and, while U-Net is strong performing consistently, it has less global context compared to transformer model types [33]. Future work will evaluate other segmentation model architectures to further improve on model performance.

Demonstrating an AI model capable of interpreting human tissue from re-perfused human cadavers “moves a step closer” to clinical applications from previous work done in tissue-mimicking phantoms [43]. Tissue-phantoms have a purpose for benchtop modeling, allowing to implement new, experimental techniques before evaluating in preclinical or clinical models [50]. However, there is a known limitation of phantom models lacking the heterogeneity of human tissue, which is captured in the cadaver model [51]. Nevertheless, the diverse data set captured for this work has its own inherent limitations. Because of the nature of the population the demographics are skewed towards older individuals who sometimes had calcified plaque visible in their vessels. While the ultimate goal is to have a generalized model that can provide accurate intervention guidance for the widest population possible, the trauma-prone demographic is often younger, e.g., military personnel. A benefit of the re-perfused model is that it provided a controlled developmental environment where the motions of interest can be isolated from the dynamic nature of live-human physiology. Establishing this baseline functionality in biological tissue serves as proof-of-concept for functionality of the AI-based clinical application.

## 5. Conclusions

This study demonstrates the feasibility of utilizing a semantic segmentation model to guide automated junctional hemorrhage control in human tissue. Even with a small dataset and generalizability challenges, the AI model was able to both find anatomical alignment and track vessel compression. Future work will focus on improving blind performance of this single segmentation AI model for implementation into a closed-loop control of a hardware prototype, delivering real-time predictions and mechanical control, to treat junctional hemorrhage injuries at or near the point of injury.

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## Abbreviations

The following abbreviations are used in this manuscript:

|       |                                               |
|-------|-----------------------------------------------|
| AI    | Artificial Intelligence                       |
| FCN   | Fully Convolutional Network                   |
| IOU   | Intersection over Union                       |
| OHARO | Office of Human and Animal Research Oversight |
| SAM   | Segment Anything Model                        |

## References

1. Eastridge, B.J.; Mabry, R.L.; Seguin, P.; Cantrell, J.; Tops, T.; Uribe, P.; Mallett, O.; Zubko, T.; Oetjen-Gerdes, L.; Rasmussen, T.E.; et al. Death on the Battlefield (2001–2011): Implications for the Future of Combat Casualty Care. *J. Trauma Acute Care Surg.* **2012**, *73*, S431–S437. [[CrossRef](#)] [[PubMed](#)]
2. Kotwal, R.S.; Howard, J.T.; Orman, J.A.; Tarpey, B.W.; Bailey, J.A.; Champion, H.R.; Mabry, R.L.; Holcomb, J.B.; Gross, K.R. The Effect of a Golden Hour Policy on the Morbidity and Mortality of Combat Casualties. *JAMA Surg.* **2016**, *151*, 15. [[CrossRef](#)] [[PubMed](#)]
3. Spiegel, S.; Baker, A.M. EMS Junctional Hemorrhage Control. In *StatPearls*; StatPearls Publishing: Treasure Island, FL, USA, 2023.
4. van Oostendorp, S.E.; Tan, E.C.T.H.; Geeraedts, L.M.G. Prehospital Control of Life-Threatening Truncal and Junctional Haemorrhage Is the Ultimate Challenge in Optimizing Trauma Care; a Review of Treatment Options and Their Applicability in the Civilian Trauma Setting. *Scand. J. Trauma Resusc. Emerg. Med.* **2016**, *24*, 110. [[CrossRef](#)] [[PubMed](#)]
5. Smith, S.; White, J.; Wanis, K.N.; Beckett, A.; McAlister, V.C.; Hilsden, R. The Effectiveness of Junctional Tourniquets: A Systematic Review and Meta-Analysis. *J. Trauma Acute Care Surg.* **2019**, *86*, 532. [[CrossRef](#)] [[PubMed](#)]
6. Gaspary, M.J.; Zarow, G.J.; Barry, M.J.; Walchak, A.C.; Conley, S.P.; Roszko, P.J.D. Comparison of Three Junctional Tourniquets Using a Randomized Trial Design. *Prehosp. Emerg. Care* **2019**, *23*, 187–194. [[CrossRef](#)] [[PubMed](#)]
7. Agarwal, R.; Niezgoda, J.; Niezgoda, J.; Madetipati, N.; Gopalakrishnan, S. Advances in Hemostatic Wound Dressings: Clinical Implications and Insight. *Adv. Skin Wound Care* **2022**, *35*, 113. [[CrossRef](#)] [[PubMed](#)]

8. Pikman Gavriely, R.; Lior, Y.; Gelikas, S.; Levy, S.; Ahimor, A.; Glassberg, E.; Shapira, S.; Benov, A.; Avital, G. Manual Pressure Points Technique for Massive Hemorrhage Control—A Prospective Human Volunteer Study. *Prehosp. Emerg. Care* **2023**, *27*, 586–591. [[CrossRef](#)] [[PubMed](#)]
9. Charlton, N.P.; Swain, J.M.; Brozek, J.L.; Ludwikowska, M.; Singletary, E.; Zideman, D.; Epstein, J.; Darzi, A.; Bak, A.; Karam, S.; et al. Control of Severe, Life-Threatening External Bleeding in the Out-of-Hospital Setting: A Systematic Review. *Prehosp. Emerg. Care* **2021**, *25*, 235–267. [[CrossRef](#)] [[PubMed](#)]
10. Avital, G.; Greenberger, C.; Kedar, A.; Pikman-Gavriely, R.; Bez, M.; Almog, O.; Benov, A. Pressure Points Technique for Traumatic Proximal Axillary Artery Hemorrhage: A Case Report. *Prehospital Disaster Med.* **2023**, *38*, 130–133. [[CrossRef](#)] [[PubMed](#)]
11. Zhang, H.; Guo, Y.; Liu, H.; Tang, H.; Li, Y.; Zhang, L. Imaging Anatomy and Surface Localization of External Control Device-Targeted Arteries for Noncompressible Torso Hemorrhage. *Mil. Med.* **2022**, *187*, e343–e350. [[CrossRef](#)] [[PubMed](#)]
12. Yan, L.; Li, Q.; Fu, K.; Zhou, X.; Zhang, K. Progress in the Application of Artificial Intelligence in Ultrasound-Assisted Medical Diagnosis. *Bioengineering* **2025**, *12*, 288. [[CrossRef](#)] [[PubMed](#)]
13. Elhaddad, M.; Hamam, S. AI-Driven Clinical Decision Support Systems: An Ongoing Pursuit of Potential. *Cureus* **2024**, *16*, e57728. [[CrossRef](#)] [[PubMed](#)]
14. Azad, R.; Aghdam, E.K.; Rauland, A.; Jia, Y.; Avval, A.H.; Bozorgpour, A.; Karimijafarbigloo, S.; Cohen, J.P.; Adeli, E.; Merhof, D. Medical Image Segmentation Review: The Success of U-Net. *IEEE Trans. Pattern Anal. Mach. Intell.* **2024**, *46*, 10076–10095. [[CrossRef](#)] [[PubMed](#)]
15. Langlotz, C.P.; Allen, B.; Erickson, B.J.; Kalpathy-Cramer, J.; Bigelow, K.; Cook, T.S.; Flanders, A.E.; Lungren, M.P.; Mendelson, D.S.; Rudie, J.D.; et al. A Roadmap for Foundational Research on Artificial Intelligence in Medical Imaging: From the 2018 NIH/RSNA/ACR/The Academy Workshop. *Radiology* **2019**, *291*, 781–791. [[CrossRef](#)] [[PubMed](#)]
16. Ma, H.; Tian, R.; Li, H.; Sun, H.; Lu, G.; Liu, R.; Wang, Z. Fus2Net: A Novel Convolutional Neural Network for Classification of Benign and Malignant Breast Tumor in Ultrasound Images. *Biomed. Eng. OnLine* **2021**, *20*, 112. [[CrossRef](#)] [[PubMed](#)]
17. Horgan, R.; Nehme, L.; Abuhamad, A. Artificial Intelligence in Obstetric Ultrasound: A Scoping Review. *Prenat. Diagn.* **2023**, *43*, 1176–1219. [[CrossRef](#)] [[PubMed](#)]
18. Hernandez Torres, S.I.; Ruiz, A.; Holland, L.; Ortiz, R.; Snider, E.J. Evaluation of Deep Learning Model Architectures for Point-of-Care Ultrasound Diagnostics. *Bioengineering* **2024**, *11*, 392. [[CrossRef](#)] [[PubMed](#)]
19. Cao, Z.; Duan, L.; Yang, G.; Yue, T.; Chen, Q. An Experimental Study on Breast Lesion Detection and Classification from Ultrasound Images Using Deep Learning Architectures. *BMC Med. Imaging* **2019**, *19*, 51. [[CrossRef](#)] [[PubMed](#)]
20. Iriani Sapitri, A.; Nurmaini, S.; Naufal Rachmatullah, M.; Tutuko, B.; Darmawahyuni, A.; Firdaus, F.; Rini, D.P.; Islami, A. Deep Learning-Based Real Time Detection for Cardiac Objects with Fetal Ultrasound Video. *Inform. Med. Unlocked* **2023**, *36*, 101150. [[CrossRef](#)]
21. Brattain, L.J.; Pierce, T.T.; Gjesteb, L.A.; Johnson, M.R.; DeLosa, N.D.; Werblin, J.S.; Gupta, J.F.; Ozturk, A.; Wang, X.; Li, Q.; et al. AI-Enabled, Ultrasound-Guided Handheld Robotic Device for Femoral Vascular Access. *Biosensors* **2021**, *11*, 522. [[CrossRef](#)] [[PubMed](#)]
22. Gjesteb, L.A.; Carruthers, A.; Werblin, J.; DeLosa, N.; Bedolla, C.; Wolak, M.; Roop, B.W.; Slavkovsky, E.; Hernandez Torres, S.I.; Amezcua, K.-L. Deep Learning-Based Tracking of Neurovascular Features Toward Semi-Automated Ultrasound-Guided Peripheral Nerve Blocks by Non-Specialists. *Bioengineering* **2026**, *13*, 556. [[CrossRef](#)] [[PubMed](#)]
23. Zhang, X.; Wang, J.; Cheng, X.; Li, J. A Review of Deep Learning-Based Medical Image Segmentation. *IET Image Process.* **2025**, *19*, e70163. [[CrossRef](#)]
24. Schwing, A.G.; Urtasun, R. Fully Connected Deep Structured Networks. *arXiv* **2015**, arXiv:1503.02351.
25. Long, J.; Shelhamer, E.; Darrell, T. Fully Convolutional Networks for Semantic Segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*; IEEE: New York, NY, USA, 2015; pp. 3431–3440.
26. Jian, J.; Xiong, F.; Xia, W.; Zhang, R.; Gu, J.; Wu, X.; Meng, X.; Gao, X. Fully Convolutional Networks (FCNs)-Based Segmentation Method for Colorectal Tumors on T2-Weighted Magnetic Resonance Images. *Australas. Phys. Eng. Sci. Med.* **2018**, *41*, 393–401. [[CrossRef](#)] [[PubMed](#)]
27. Alkassar, S.; Abdullah, M.A.; Jebur, B.A. Automatic Brain Tumour Segmentation Using Fully Convolution Network and Transfer Learning. In *Proceedings of the 2019 2nd International Conference on Electrical, Communication, Computer, Power and Control Engineering (ICECCPCE)*; IEEE: New York, NY, USA, 2019; pp. 188–192.
28. Yang, H.; Shan, C.; Kolen, A.F.; de With, P.H. Efficient Catheter Segmentation in 3D Cardiac Ultrasound Using Slice-Based FCN with Deep Supervision and F-Score Loss. In *Proceedings of the 2019 IEEE International Conference on Image Processing (ICIP)*; IEEE: New York, NY, USA, 2019; pp. 260–264.
29. Ronneberger, O.; Fischer, P.; Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 234–241.

30. Jain, P.K.; Dubey, A.; Saba, L.; Khanna, N.N.; Laird, J.R.; Nicolaides, A.; Fouda, M.M.; Suri, J.S.; Sharma, N. Attention-Based UNet Deep Learning Model for Plaque Segmentation in Carotid Ultrasound for Stroke Risk Stratification: An Artificial Intelligence Paradigm. *J. Cardiovasc. Dev. Dis.* **2022**, *9*, 326.
31. Al-Zogbi, L.; Raina, D.; Pandian, V.; Fleiter, T.; Krieger, A. Robotic Ultrasound-Guided Femoral Artery Reconstruction of Anatomically-Representative Phantoms. In *Proceedings of the 2025 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*; IEEE: New York, NY, USA, 2025; pp. 4010–4017.
32. Holland, L.; Hernandez Torres, S.I.; Snider, E.J. Using AI Segmentation Models to Improve Foreign Body Detection and Triage from Ultrasound Images. *Bioengineering* **2024**, *11*, 128. [[CrossRef](#)] [[PubMed](#)]
33. Yao, W.; Bai, J.; Liao, W.; Chen, Y.; Liu, M.; Xie, Y. From CNN to Transformer: A Review of Medical Image Segmentation Models. *J. Imaging Inform. Med.* **2024**, *37*, 1529. [[CrossRef](#)] [[PubMed](#)]
34. Zhou, Z.; Rahman Siddiquee, M.M.; Tajbakhsh, N.; Liang, J. UNet++: A Nested U-Net Architecture for Medical Image Segmentation. In *Proceedings of the Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, 20 September 2018; Volume 11045*, pp. 3–11. [[CrossRef](#)] [[PubMed](#)]
35. Khan, R.F.; Lee, B.-D.; Lee, M.S. Transformers in Medical Image Segmentation: A Narrative Review. *Quant. Imaging Med. Surg.* **2023**, *13*, 8747767. [[CrossRef](#)] [[PubMed](#)]
36. Chen, J.; Lu, Y.; Yu, Q.; Luo, X.; Adeli, E.; Wang, Y.; Lu, L.; Yuille, A.L.; Zhou, Y. Transunet: Transformers Make Strong Encoders for Medical Image Segmentation. *arXiv* **2021**, arXiv:210204306.
37. Chen, J.; Mei, J.; Li, X.; Lu, Y.; Yu, Q.; Wei, Q.; Luo, X.; Xie, Y.; Adeli, E.; Wang, Y. TransUNet: Rethinking the U-Net Architecture Design for Medical Image Segmentation through the Lens of Transformers. *Med. Image Anal.* **2024**, *97*, 103280. [[CrossRef](#)] [[PubMed](#)]
38. Zhu, Z.; Sun, M.; Qi, G.; Li, Y.; Gao, X.; Liu, Y. Sparse Dynamic Volume TransUNet with Multi-Level Edge Fusion for Brain Tumor Segmentation. *Comput. Biol. Med.* **2024**, *172*, 108284. [[CrossRef](#)] [[PubMed](#)]
39. Cao, H.; Wang, Y.; Chen, J.; Jiang, D.; Zhang, X.; Tian, Q.; Wang, M. Swin-Unet: Unet-like Pure Transformer for Medical Image Segmentation. In *Proceedings of the European Conference on Computer Vision*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 205–218.
40. Gomes, R.; Pham, T.; He, N.; Kamrowski, C.; Wildenberg, J. Analysis of Swin-UNet Vision Transformer for Inferior Vena Cava Filter Segmentation from CT Scans. *Artif. Intell. Life Sci.* **2023**, *4*, 100084. [[CrossRef](#)]
41. Kirillov, A.; Mintun, E.; Ravi, N.; Mao, H.; Rolland, C.; Gustafson, L.; Xiao, T.; Whitehead, S.; Berg, A.C.; Lo, W.-Y.; et al. Segment Anything. *arXiv* **2023**, arXiv:2304.02643.
42. Avital, G.; Hernandez Torres, S.I.; Knowlton, Z.J.; Bedolla, C.; Salinas, J.; Snider, E.J. Toward Smart, Automated Junctional Tourniquets—AI Models to Interpret Vessel Occlusion at Physiological Pressure Points. *Bioengineering* **2024**, *11*, 109. [[CrossRef](#)] [[PubMed](#)]
43. Hernandez Torres, S.I.; Winter, T.; Mejia, I.; Bedolla, C.; Alexander, B.; Collier, J.P.; Lopez, M.D.; Snider, E.J. Smart, Automated Junctional Tourniquets Leveraging AI-Driven Ultrasound Guidance. *Sci. Rep.* **2026**, *16*, 6865. [[CrossRef](#)] [[PubMed](#)]
44. Badrinarayanan, V.; Kendall, A.; Cipolla, R. SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* **2016**, *39*, 2481–2495. [[CrossRef](#)] [[PubMed](#)]
45. Kingma, D.P.; Ba, J. Adam: A Method for Stochastic Optimization. *arXiv* **2017**, arXiv:1412.6980.
46. Eigen, D.; Fergus, R. Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture. In *Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV)*; IEEE: Santiago, Chile, 2015; pp. 2650–2658.
47. Wohlgemut, J.M.; Pisirir, E.; Stoner, R.S.; Kyrimi, E.; Christian, M.; Hurst, T.; Marsh, W.; Perkins, Z.B.; Tai, N.R.M. Identification of Major Hemorrhage in Trauma Patients in the Prehospital Setting: Diagnostic Accuracy and Impact on Outcome. *Trauma Surg. Acute Care Open* **2024**, *9*, e001214. [[CrossRef](#)] [[PubMed](#)]
48. Malik, A.N.; Rowland, J.; Haber, B.D.; Thom, S.; Jackson, B.; Volk, B.; Ehrman, R.R. The Use of Handheld Ultrasound Devices in Emergency Medicine. *Curr. Emerg. Hosp. Med. Rep.* **2021**, *9*, 73–81. [[CrossRef](#)] [[PubMed](#)]
49. Hernandez Torres, S.I.; Holland, L.; Winter, T.; Ortiz, R.; Amezcua, K.-L.; Ruiz, A.; Thorpe, C.R.; Snider, E.J. Real-Time Deployment of Ultrasound Image Interpretation AI Models for Emergency Medicine Triage Using a Swine Model. *Technologies* **2025**, *13*, 29. [[CrossRef](#)]
50. Jawli, A.; Aldehani, W.; Nabi, G.; Huang, Z. Tissue-Mimicking Material Fabrication and Properties for Multiparametric Ultrasound Phantoms: A Systematic Review. *Bioengineering* **2024**, *11*, 620. [[CrossRef](#)] [[PubMed](#)]
51. Gates, K.; Baer, L.; Holcomb, J.B. Prehospital Emergency Care: Evaluation of the Junctional Emergency Tourniquet Tool with a Perfused Cadaver Model. *J. Spec. Oper. Med.* **2014**, *14*, 40–44. [[CrossRef](#)] [[PubMed](#)]

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