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Automatic detection of cotton balls during brain surgery: Where deep learning meets ultrasound imaging to tackle foreign objects

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Abstract

Cotton balls are a versatile and efficient tool commonly used in neurosurgical procedures to absorb fluids and manipulate delicate tissues. However, the use of cotton balls is accompanied by the risk of accidental retention in the brain after surgery. Retained cotton balls can lead to dangerous immune responses and potential complications, such as adhesions and textilomas.

In a previous study, we showed that ultrasound can be safely used to detect cotton balls in the operating area due to the distinct acoustic properties of cotton compared with the acoustic properties of surrounding tissue. In this study, we enhance the experimental setup using a 3D-printed custom depth box and a Butterfly IQ handheld ultrasound probe. Cotton balls were placed in variety of positions to evaluate size and depth detectability limits. Recorded images were then analyzed using a novel algorithm that implements recently released YOLOv4, a state-of-the-art, real-time object recognition system. As per the radiologists' opinion, the algorithm was able to detect the cotton ball correctly **61%** of the time, at approximately 32 FPS. The algorithm could accurately detect cotton balls up to 5mm in diameter, which corresponds to the size of surgical balls used by neurosurgeons, making the algorithm a promising candidate for regular intraoperative use.

Keywords

Deep learning; object detection; neuroimaging; recognition system; retained foreign object; ultrasound

I. INTRODUCTION

Cotton balls are crucial surgical adjuncts. They are used to stop bleeding (hemostasis) and improve visualization around critical structures during neurosurgical procedures. However, the small size and visual similarity between the cotton and surrounding tissue can make them difficult to identify, which increases the risk of accidental retention after surgery (Fig. 1). Retained cotton balls can cause significant foreign body reactions, such as a benign fibrous tissue reaction, or abscess formation [1]. Such complications have different clinical and radiological characteristics but often require a follow-up surgical intervention that carries additional risk.

Since 1973, 50 cases of intracranial textiloma have been recorded [2,3]. Because the incidence of retained cotton is likely underreported, the true frequency of these events is unknown [2]. However, approximately half of malpractice cases involve retained foreign objects, and these cases can result in costly lawsuits for hospitals [2]. At present, there is no reliable means of detection for retained cotton balls before surgical closure, and previous reports emphasize the need for meticulous irrigation and inspection of the operative site prior to closure [1].

The serious costs and complications involved in foreign object retention emphasize the vital need for a solution that allows surgeons to identify foreign bodies during neurosurgical procedures. Due to the specific nature of these procedures, it is important that potential solutions must be production-ready and suitable for fast, accurate real-time detection, aligning with the strengths of a single-stage object detection system. Ultrasound imaging is one of the most commonly used medical imaging modalities due to its cost-efficiency, portability, and non-ionizing nature [3]. Using ultrasound imaging to detect the presence of cotton on a surface level has shown a noticeable difference in cotton and brain tissue based on acoustic characteristics and contrast, thereby allowing ultrasound imaging to be a viable modality for object detection [4].

The rapid development of data-driven approaches and machine learning methods in recent years has considerably improved computer-aided detection and diagnosis algorithms. The three major components of computer-aided medical image analysis are detection, classification, and segmentation [5]. Assigning a class label to an image is referred to as image classification, whereas drawing a boundary box around one or more objects in an image represents object localization. Object detection, then, involves both tasks: it refers to drawing a bounding box around each object of interest in the image, and assigning them a class label. This process is called *object recognition*. The field of object detection is particularly advanced due to modern technological developments, and will be the focus of this study [6]. Currently, there are two types of one-stage object detection systems: YOLO (You Only Look Once) [7] and SSD (Single shot detector). The remaining detection systems

have two stages, such as the faster R-CNN (Region-based Convolutional Neural Networks) [8]. Two-stage detection algorithms generally provide more accurate detections, albeit at a higher cost. They are composed of the region proposal stage, which is followed by area classification and refinement. Region proposal is used to identify possible locations of the target in the figure in advance. Unlike two-stage systems, single-stage algorithms bypass the initial region-proposal stage and generate category prediction and localization trading off detection accuracy for increased detection speed [9].

This study presents a YOLOv4-arch model that can accurately locate cotton during neurosurgical procedures, thereby minimizing the risk of cotton retention (Fig. 2). In order to train our YOLOv4 model, we developed an extensive dataset of ultrasound images of brain tissue. Both humans and swine have gyrencephalic brains—that is, the cerebral cortex has convolutions and is not smooth. Humans and swine also have a comparable white-to-gray matter ratio and size, making swine tissue an accurate and translatable model when compared with alternative animal models (eg, rodents).

Cotton balls of varying size, shape, and absorption levels were placed within swine brain tissue to develop a dataset of 5,000 ultrasound images for training and testing of the YOLOv4 architecture. Cotton balls were identified by acoustic enhancement in the shape of a light gray object with higher contrast compared with the otherwise dark grey surrounding tissue. The training and validation sets were built using images that were carefully annotated using known characteristics and visual differences in cotton and brain tissue.

II. METHODS

1. Experimental setup

In order to simulate a neurosurgical setting, different combinations of size and location for the cotton balls were used. To preserve the shape and structure of the brain parenchyma, a 3D SOLIDWORKS model of a cylindrical container was designed with diameter of 15 cm, thickness of 1.5 cm, and a wide base for increased stability (Fig. 3). In addition, 1 × 1 × 0.2 cm markings on the outer surface of the container at equal increments of 2cm from the base were designed. The container was then printed at the Johns Hopkins University Biomedical Engineering Design Lab using The Object 3D printer, and the material used was Vero Clear. The transparent finish along with the markings allowed for the visualization of the cotton ball from the outside, enabling manual identification of its position and placement.

Freshly euthanized pig brains were bought from Wagner Meats market in Mt. Airy, MD. These samples, sliced into hemispheres, were used within 6 hours of euthanasia to ensure the parenchymal hemispheres were intact to simulate physiological settings. Ultrasound imaging was performed using a portable Butterfly IQ ultrasound probe operating at 5 MHz. The location of the probe was maintained using a clamp and flexible gooseneck apparatus to reduce noise in the image induced by hand movement.

After placing the brain samples into the container, saline was injected to fill any air pockets. Commercially available sterile cotton balls were cut into 2cm diameter pieces and soaked in saline. The cotton ball was then placed below the brain inside the 3D printed container, and

the holder was moved to position the probe in a way that just touched the sample surface. Figure 4 shows the experimental setup.

To find the smallest detectable cotton ball, a size test was performed. Cotton balls with diameters of 20mm, 15mm, 10mm, 5mm, 3mm and 2mm were cut and soaked in saline. The rest of the experimental setup was unchanged. These cotton balls were then placed under the brain sample and imaged.

Similarly, a depth test was performed to evaluate the maximum depth at which cotton balls can be detected. A 15mm diameter cotton ball was first placed under one brain sample and images were obtained. Next, one more layer of porcine brain, with a thickness of 2cm, was add to the container, thereby doubling the amount of brain tissue over the cotton ball. This was repeated until 4 layers, or a total of 8cm of tissue, was added above the cotton ball. This depth was in accordance with neurosurgical procedures. Photos and video of the ultrasound results were recorded.

2. Deep Learning: Network Architecture

This study showcases the implementation of a YOLOv4 model to detect cotton localization within brain tissue. Convolutional Neural Networks (CNNs) are a class of deep neural networks commonly used for image visualization and analysis. YOLO, a single-stage CNN, can simultaneously generate category localization and probabilities. The YOLOv4 architecture is the latest iteration of the YOLO line, featuring a more robust object detection solution with improved detection performance and speed compared to competing models such as the Fast R-CNN [8]. As a single-stage object detector, the YOLO model's architecture is composed of a backbone, neck, and head (Fig. 5).

A backbone is a pre-trained model that functions as the feature extractor of the CNN. For the GPU-based version of YOLOv4, which was utilized for this experiment, the backbone model is the **CSPDarknet53**, which is shown to outperform its competitors (eg, EfficientNet-B3 and CSPResNext50) in terms of object detection. The head is the component used to predict classes and bounding boxes. YOLOv4 implements the same anchor-based head as **YOLOv3** [10]. The neck refers to the additional layers between the backbone and the head, and is often used to extract different feature maps from varying stages of the backbone process. YOLOv4 uses the **Spatial Pyramid Pooling (SPP)** and **Path Aggregation Network (PANet)**. Both are added over the CSPDarknet53 layer as they efficiently increase the neck receptive field, thereby improving the model accuracy while bearing no impact on the computation time [11,12].

3. Dataset Preprocessing and Data Augmentation

All images were scaled to a common size of 416 × 416 pixels. Contrast preprocessing was used to define clearer edges, exaggerating neighboring pixel intensity difference to improve the visibility of cotton within neural tissue. For data augmentation, pre-built contributions within the YOLOv4 framework were used (also known as the BoS/BoF). Self-adversarial training (SAT) was used to improve the detection performance of the model. SAT is a data-augmentation technique that uses back-propagation to determine model

vulnerabilities. Additionally, random erase, a technique that replaces regions within images with randomized values to prevent the model from overfitting, was also used. This series of steps improved the model's performance for specific user cases without introducing further delay.

For the YOLOv4 configuration, the base hyper-parameters as suggested in the Darknet Repository were used for a single class. The architecture was trained using a single GPU, and we experimented with various BoS modules, as provided within the framework. For our model training, we utilized Google's Colab Notebooks, a Jupyter notebook environment that runs entirely on the cloud. The model was trained on the standard single Tesla K80 GPU that is provided with the virtual machine.

III. RESULTS

A previous study investigated three different modalities for identifying cotton balls. For modalities that used imaging contrast dyes, ultrasound imaging, and radiographic CT scan, ultrasound imaging showed the most promise [3]. In concordance with our previous results, ultrasound imaging was able to detect surgical cotton balls in porcine brain parenchyma successfully in this study. Acoustic enhancement coupled with distal shadowing and distinctly increased contrast made the cotton balls stand out from the surrounding image, which was mainly dark or sparsely populated with tones of grey. The image properties of cotton stayed consistent regardless of the location of the cotton ball in respect to the brain tissue depth.

Analysis was performed on video clips in different configurations of cotton ball position. Video clips were about 10 seconds in length. In total, 13 clips were evaluated by 2 different radiologists who were blinded to the configurations. Physicians were chosen based on their availability and familiarity with the topic of interest. The individual ratings of each video clip are presented in Table 1. Ratings were based on the physician's ability to read the images as well as the algorithm's accuracy to detect and correctly identify the cotton ball. Based on these ratings, the system achieved an accuracy of 54% according to one physician and 69% accuracy according to the second, averaging to a total accuracy of 61%.

Seven of 13 clips received unanimous true positive ratings from both physicians. These corresponded to the size tests wherein the size of the cotton balls was varied (Fig. 6). The possible reason for the positive results of the size test could be the clear contrast between the cotton ball and the surrounding brain parenchyma, enhanced by increasing the diameter of the ball. The scope of additional artifacts in this setting was also low, thus rendering a clear image of the cotton ball easily identified by both the physicians and the system.

Based on our informal conversations with numerous neurosurgeons who use cotton balls regularly for brain surgeries, the size of surgical cotton balls depends on the surgeon's preference and technician's precision. Nevertheless, on average, the diameter of the cotton balls ranges from 20mm to 5mm (Fig. 6(a), 6(d)), corresponding precisely to the size range tested in this study. This implies that our algorithm can accurately detect most surgical

cotton balls used in daily practice, making it a valuable addition for the use of ultrasound procedures during routine surgeries.

The clips that received negative ratings mostly corresponded to the depth tests in which the number of brain parenchyma above and below the cotton ball were varied. Figures 7(e) and 7(f) show the results obtained for depth tests with 2 and 3 brain layers, respectively. In both the cases, the annotation box highlights areas that may or may not contain the cotton ball, as per the radiologists' opinions. In cases corresponding to a false positive outcome, the error often occurred because the algorithm identified an echogenic area, which could have been air or artifacts. This could be because the additional tissue above the cotton balls introduced air gaps and artifacts, which are easily mistaken for a cotton ball by the system due to the similarity in their contrasts. Although saline was injected to fill air gaps, there is still a possibility that additional air pockets might have been introduced due to the stacking of the brain tissue layers.

A major limitation of this study is that the algorithm was trained only for positive cases—in other words, the cotton ball was present in every trial. This might have introduced the false positive error, meaning that the algorithm is directed to always search for a cotton ball, even when one is not present. To overcome this limitation, a greater number of trials needed to be conducted, and the algorithm would need to be trained on true negative cases as well. This would reduce the chance of error. Once the algorithm is appropriately trained, randomized trials with or without the cotton ball can be presented to both the algorithm and the radiologists and its true performance against human intelligence would be determined.

One way to overcome current limitations of the study would be to conduct further trials, in which the position and size of the cotton ball would be individually varied. Similarly, the depth test could be repeated by increasing the number of brain layers and placing the cotton ball in between layers. These additional tests would also increase the number of still images manifold and help train the model to improve the accuracy of cotton-ball detection. Another option would be to use ultrasound probes of different specifications, especially varying frequencies in order to improve the precision required to detect smaller cotton balls or cotton balls placed at deeper depths.

IV. CONCLUSIONS

This study demonstrates that ultrasound is a potential solution to accidentally retained cotton balls. The YOLOv4 architecture shows early promise in using ultrasound images to identify cotton balls in the operative field during neurosurgical procedures. Based on the radiologists' feedback, the algorithm could correctly identify cotton balls 61% of the times. The algorithm performed better while detecting cotton balls of different sizes, compared with detecting cotton balls situated beneath more than one layer of brain. Future work should focus on improving accuracy using different ultrasound probes, increasing the number of experiments, and obtaining more images to enhance training of the algorithm. The algorithm needs further training with respect to the absence of cotton balls, and human vs machine intelligence would then need to be compared. In conclusion, our study presents

a building block toward the use of artificial intelligence for ultrasound imaging and accurate foreign object detection.

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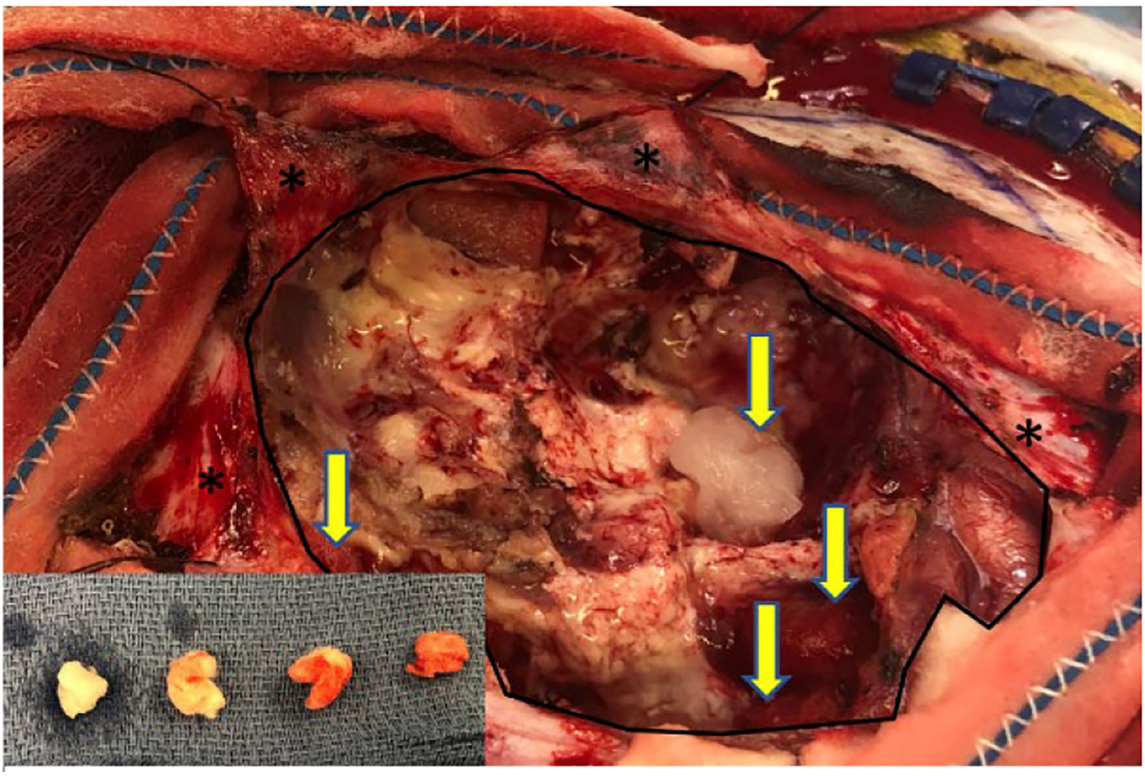

Figure 1: Intraoperative photography during redo surgery

performed for lesional intractable epilepsy highlighting the difficult identification of cotton balls (yellow arrow) in the resection cavity (outlined by the black line). The similarity between the blood-soaked cotton-balls and surrounding tissue can make their visualization challenging; the cotton balls removed from the surgical field are portrayed in the inset. Black asterix (*) represents the dura mater. Figure is taken with permission from SDR and CDG.

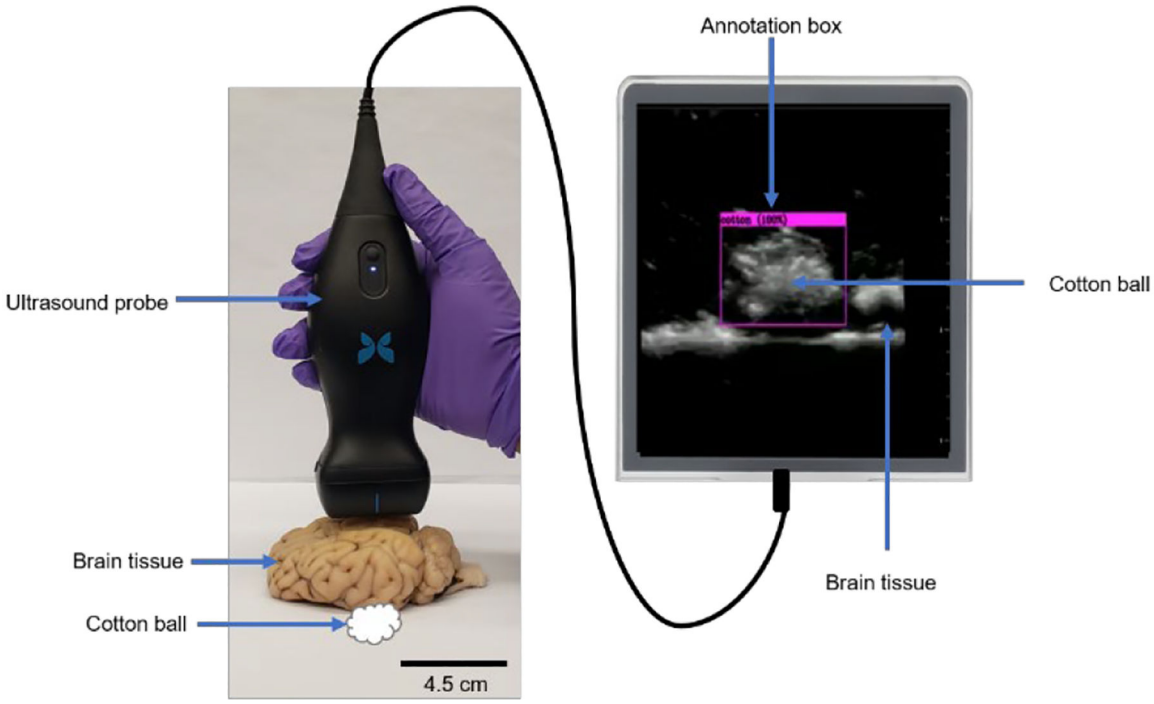

Figure 2: Automatic detection of cotton balls using the Butterfly IQ Ultrasound probe.
Concept image depicts the experimental setup using a cotton ball placed beneath a porcine brain and imaged using a handheld ultrasound probe. The goal is to have an integrated ultrasound imaging interface that can image and detect surgical cotton balls without human intervention, thus reducing the chance of their accidental retention

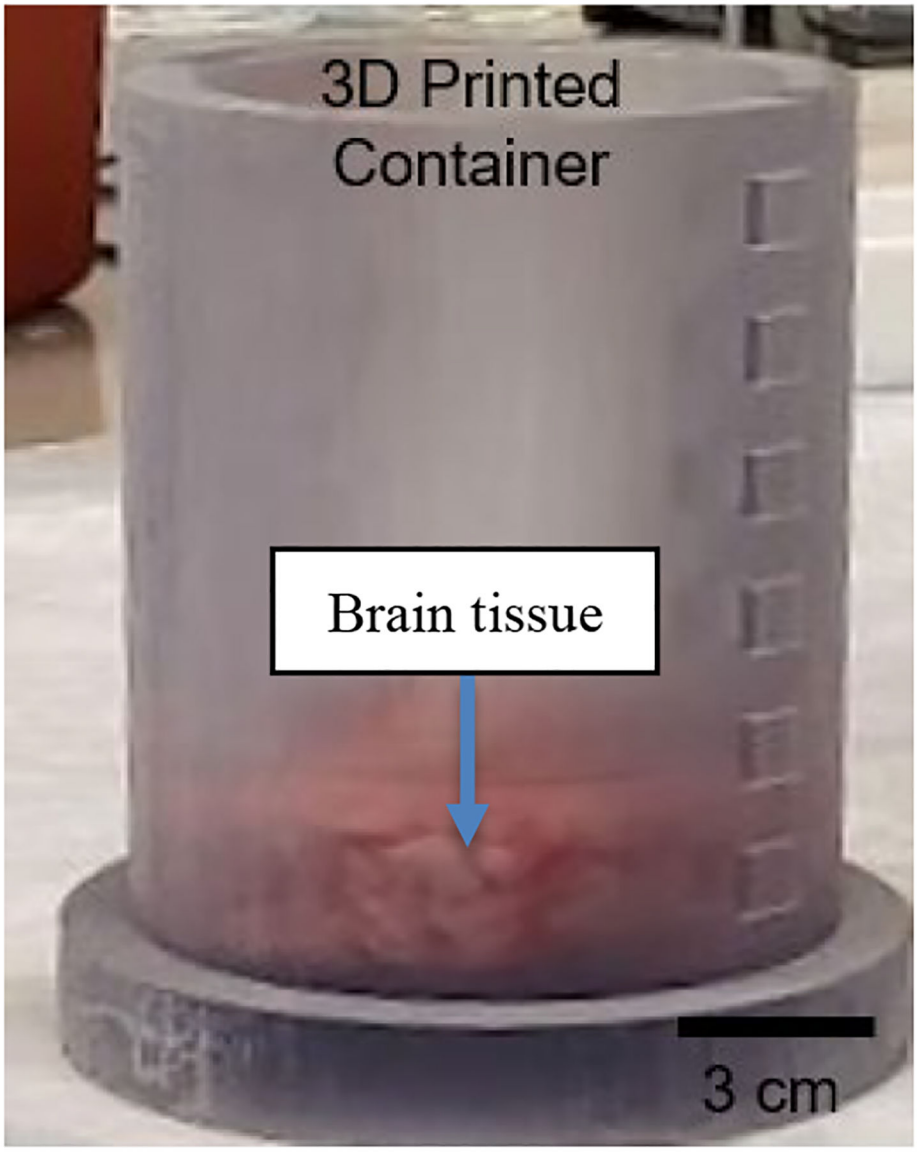

Figure 3:
3D-printed transparent depth box

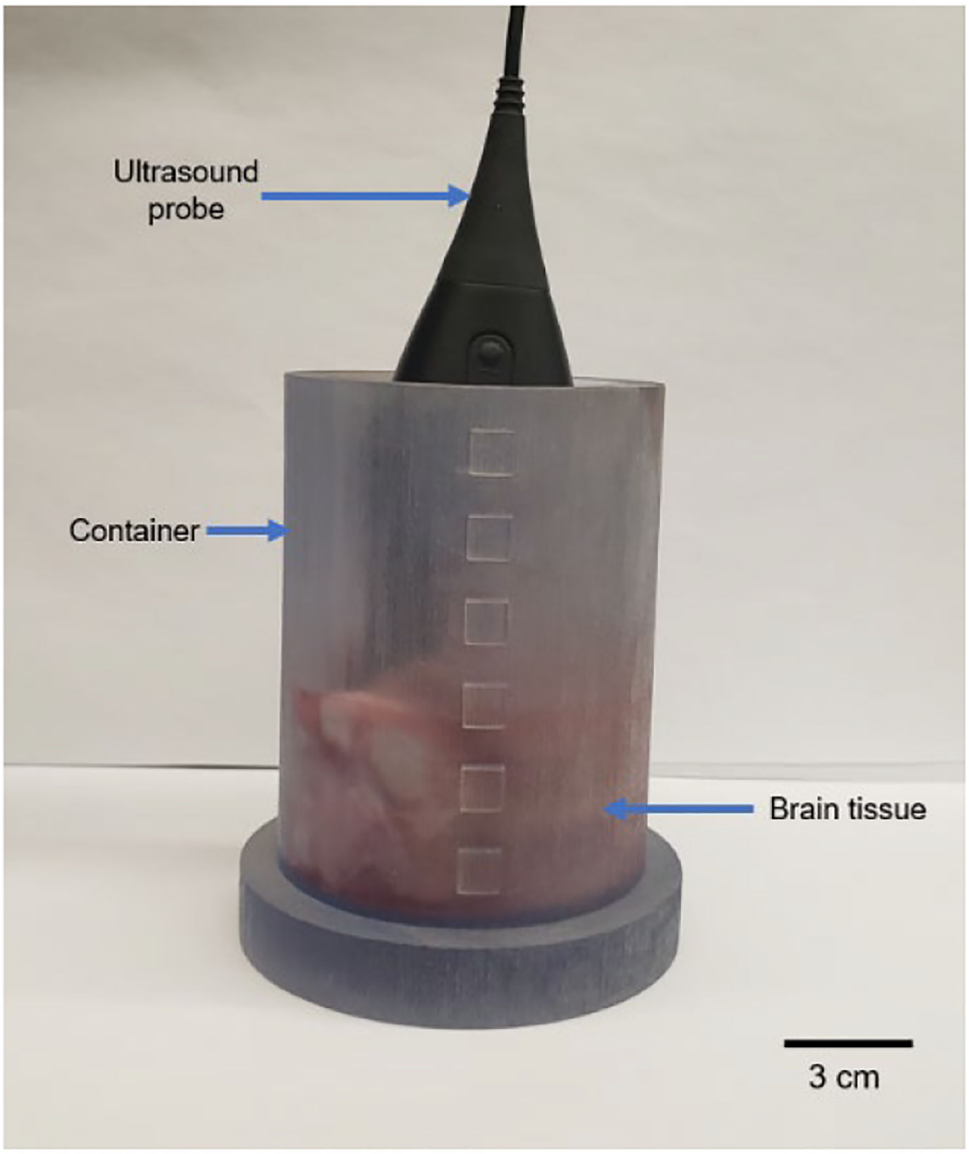

Figure 4: The experimental setup.

The porcine brain sample was placed in the 3D-printed depth box and injected with saline. A Butterfly IQ Ultrasound probe was used for imaging. Surgical cotton balls were then soaked in saline and placed in different configurations in and around the brain tissue.

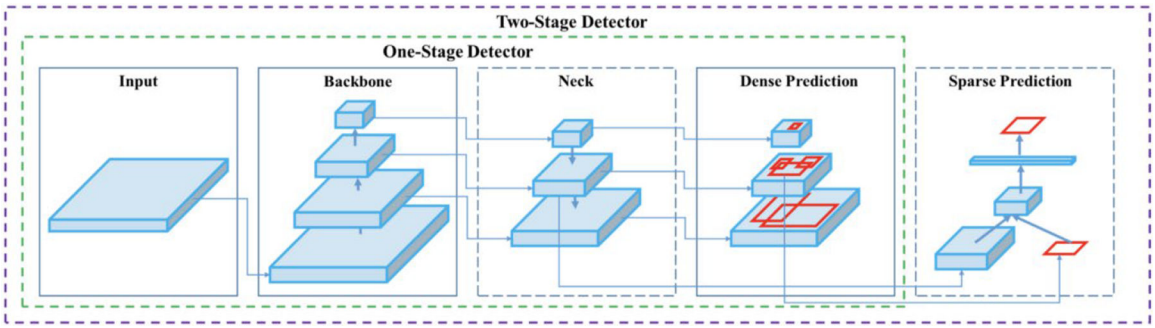

Figure 5:
Architecture of the YOLO model, consisting of the backbone, neck and head

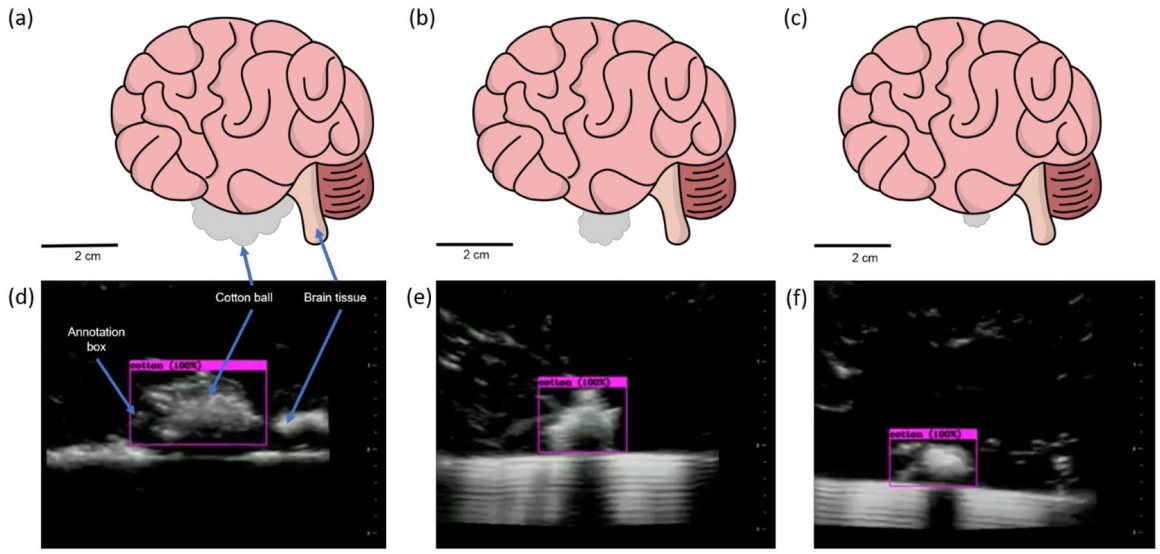

Figure 6: Concept image and results for experiment using cotton balls of different sizes below the brain.

Concept images for experiments run using cotton balls with diameters ranging in size from **(a)** 20 mm, **(b)** 10 mm, and **(c)** 5 mm. Images corresponding for cotton balls of size 20mm, 10 mm, and 5mm are shown in **(d)**, **(e)** and **(f)**, respectively. Cotton (light gray) is distinguishable from its surrounding tissue (black/dark gray) in the ultrasound image.

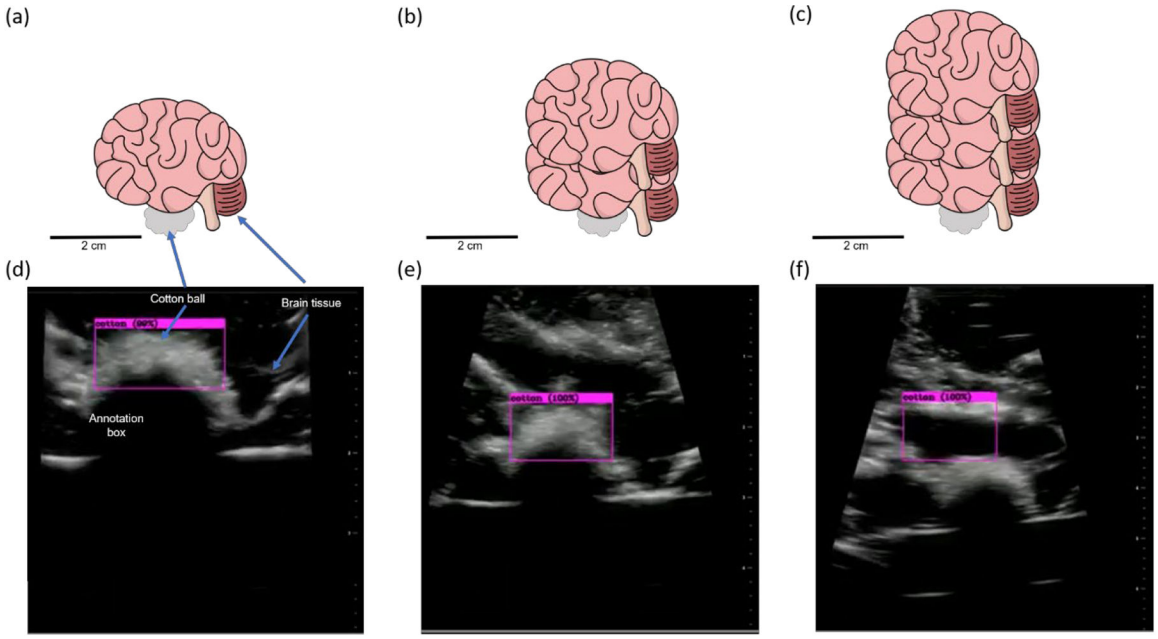

Figure 7: Concept image and results for experiment using cotton balls and different layers of brain stacked above.

Concept images for experiments run using cotton balls below the brain surface in the depth box at depths beneath the surface **(a)** 2 cm, **(b)** 4 cm, and **(c)** 6 cm. Images corresponding for cotton balls beneath 1, 2 and 3 brain layers are shown in **(d)**, **(e)** and **(f)**, respectively). Cotton (light gray) is distinguishable from its surrounding tissue (black/dark gray) in the ultrasound image. However, the algorithm could not identify the balls as efficiently as it could in the size test.

Table 1:

Physicians' ratings of the 13 video clips containing ultrasound images of the cotton balls along with an annotation box highlighting the cotton ball.

Video description	PHY-1	PHY-2	Video description	PHY-1	PHY-2
20mm ball on top of 1 brain	True −	False +	Size test: 10mm	True +	True +
20mm ball on top of 1 brain	False +	True +	Size test: 5mm	True +	True +
20mm ball below 1 brain	False +	True +	Size test: 3mm	True +	True +
20mm ball on top of 1 brain	True +	True +	Depth test: 1 brain layer	False +	False +
Ball in between 2 brains	True +	True +	Depth test: 2 brain layers	False +	False +
Size test: 20mm	True +	True +	Depth test: 3 brain layers	False +	False +
Size test: 15mm	True +	True +			