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Artificial Intelligence in Health

ORIGINAL RESEARCH ARTICLE

Leveraging the smarts in your phone: An artificial intelligence-driven iOS application for neurosurgical navigation of external ventricular drains

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Abstract

External ventricular drain (EVD) placement is a critical neurosurgical procedure traditionally performed freehand, with inherent risks of malposition, infection, and hemorrhage. Recent advances in artificial intelligence (AI), particularly in medical imaging and real-time computer vision, have enabled the development of portable navigation tools that may enhance accuracy, safety, and bedside accessibility. This study evaluated whether iOS devices equipped with a TrueDepth camera could perform real-time object and facial recognition, tracking, and semantic segmentation of computed tomography (CT) scans for non-immobilized heads to guide EVD placement via a custom AI-driven application. A custom iOS application was developed to provide a complete, real-time surgical navigation experience on an iPhone or iPad Pro. Three AI models were trained, tuned, and validated: a semantic segmentation model for brain anatomy, a semantic segmentation model for facial features, and an object detection model for a custom EVD stylet attachment. GPU programming accelerated on-device real-time, continuous registration while optimizing power consumption. A UNet convolutional neural network trained on eight 1 mm head CTs achieved 98.3% testing and 98.2% validation accuracy using a 50/50 test–validation split, segmenting a thin-cut CT in 3 s on an iPhone 12 Pro. Point cloud merging of patient anatomy took 4 seconds with an initial depth scan of 30,000 points, updating in real time with a cumulative error of 1×10^{-8} cm. Transfer learning-powered EVD tracking, trained for 1,000 epochs, achieved an intersection over union of 1.0 and 0.98 for the detection model, with inference times of 800 μs on Apple's Neural Engine. This feasibility study demonstrates that iOS devices with TrueDepth cameras can enable real-time, continuous surgical navigation for EVD stylets.

Keywords: External ventricular drain; Surgical navigation; Artificial intelligence; Machine learning

1. Introduction

Surgical navigation has become a crucial tool in neurosurgery, enabling accurate localization and targeting of lesions within the brain and spine to improve surgical precision and patient outcomes.[1-3] While traditional navigation methods relied on intraoperative imaging, computer-assisted navigation systems have become increasingly common and popular.[4-7] These systems, however, typically require costly, proprietary computing to run navigation software and are often bulky and cumbersome.

Innovations in computation, particularly artificial intelligence (AI), have paved the way for the development of higher-accuracy, lower-cost navigation techniques. Convolutional neural networks (CNNs), in particular, have revolutionized image recognition across industries, including neurosurgery.[8-10] CNNs are neural network-based machine learning, also known as deep learning models, that are now the standard for computer vision, particularly for identifying and recognizing objects or features via pixel analysis.[11-13] In neurosurgery, CNN applications include, but are not limited to, automatic segmentation of vertebral bodies and intervertebral discs in magnetic resonance imaging (MRI)[14-17] and computed tomography (CT),[18] measurement of Cobb angles from X-rays,[19,20] diagnosis of vertebral fractures,[21] enhanced diagnosis and classification of brain tumors,[22,23] and intraoperative co-registration of two-dimensional and three-dimensional (3D) imaging.[24] AI-based navigation software powered by U-Net can improve efficiency and performance, potentially eliminating the need for expensive, cumbersome hardware in the operating room or at the bedside.

More recently, augmented reality (AR) has emerged as a valuable tool for facilitating surgical care in the operating room and beyond. AR merges real-world images with virtual objects generated by computer graphics in real time.[25] In the operating room, AR has found applications in visualizing tumors and surrounding anatomical structures in a number of oncological settings to facilitate safe resection.[26-34] In neurosurgery, AR applications include guiding pedicle screw placement in spine surgery and visualizing anatomy during minimally invasive surgery.[35-38] Outside the operating room, AR has proven effective in surgical and medical education, including virtual surgical training.[39,40]

Bedside neurosurgical procedures represent a setting where such navigational innovations could be particularly beneficial, as limited space and urgent or emergent scenarios often preclude the use of traditional operating room stereotactic setups. One such urgent or emergent, historically blind-placement procedure is external ventricular drain (EVD) insertion. An EVD is a temporary catheter system inserted into the cerebral ventricles to divert cerebrospinal fluid (CSF) for both therapeutic and diagnostic purposes. It is most commonly used to manage elevated intracranial pressure in conditions such as subarachnoid hemorrhage, traumatic brain injury, and hydrocephalus.[41] EVDs allow continuous monitoring of intracranial pressure and facilitate sampling of CSF to guide treatment of structural obstructions, hemorrhage-related complications, and other conditions.[42]

The placement procedures involve incising the scalp and drilling a small burr hole, typically at Kocher's point—approximately 10–11 cm posterior to the nasion and 2–3 cm lateral to the midline—followed by careful advancement of a catheter 6–7 cm until CSF return is noted. This location is presumed to be in the ipsilateral lateral ventricle near the foramen of Monro, which connects the lateral ventricles to the inferior third ventricle.[43] The catheter is then tunneled subcutaneously for at least 6 cm to reduce infection risk, secured with stitches or staples, and connected to an external drainage and intracranial pressure monitoring system. Most institutions confirm placement with a post-operative brain CT scan[43] (Figure 1). Despite its ubiquity in neurocritical care, EVD placement carries notable risks, including hemorrhage, infection, and malposition. Misplacement of EVDs is associated with higher infection and hemorrhage rates, the need for revision procedures, increased healthcare costs, and prolonged hospital stay (PMID: 36434852).[41]

EVD placement has the potential to be optimized by AI-based neuronavigation. AI navigation tools have already been integrated into other specialties for bedside procedures, such as ultrasound-guided vascular access and

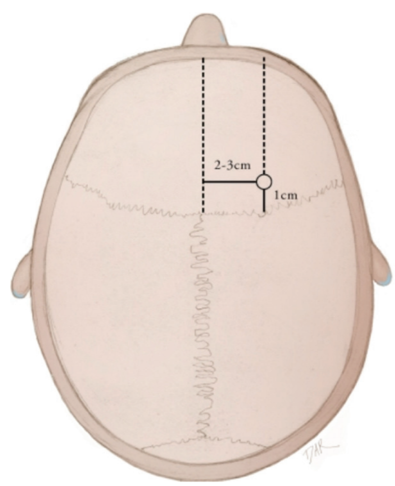

Figure 1. Landmarks for external ventricular drain placement. The classic trajectory is Kocher's point, 11–12 cm behind the nasion on the mid-pupillary line, 1 cm anterior to the palpated coronal suture, with a trajectory orthogonal to the ipsilateral medial canthus and ipsilateral tragus.

portable diagnostic imaging.[44] The iOS-based platform presented in the present study could similarly serve as a foundational tool in resident education by providing real-time, immersive feedback on trajectory and depth during catheter placement. Coupled with the low hardware footprint of smartphones, it allows for seamless integration of safety and navigation features without imposing a significant burden on workflow or cost.

The cognitive load and decision-making complexity inherent in high-stakes procedures such as EVD placement are often underestimated, particularly for junior providers, trainees, or advanced practitioners who perform the procedure infrequently. AI-based systems can alleviate some of this procedural burden by offering real-time alignment cues, trajectory verification, and visual reinforcement through augmented overlays. This human–machine collaboration reduces reliance on rote memorization or abstract spatial reasoning, thereby lowering error rates, especially during periods of fatigue, night shifts, or acute crisis scenarios.

The present study seeks to investigate whether a custom-designed AI application for mobile devices, specifically an iOS device equipped with a TrueDepth camera, can provide instantaneous navigation by identifying and tracking an EVD stylet in real time, with potential future application as a bedside navigation tool. We developed an iOS application leveraging the optimized computational hardware of Apple devices and performed simulated navigated procedures on specific models (iPhone 12 Pro, 13 Pro, 14 Pro, and M1 and M2 iPad Pro). We evaluated whether these devices could meet the computational requirements for computer-assisted navigation, the resolution and accuracy they could achieve, and the technical feasibility of performing these procedures on battery-powered devices. Accuracy was then compared to that of a traditional navigation system. We hypothesize that our custom application will provide real-time, accurate surgical navigation on an iPhone, encouraging further exploration of its use in EVD placement and other cranial neurosurgical procedures both at the bedside and in the operating room. The ultimate goal of this investigation is to integrate existing technologies in registration and object tracking into a single custom application capable of performing EVD navigation on an iOS device at the bedside, thereby enabling timely neurosurgical navigation without requiring a complex setup that delays urgent or emergent patient care.

2. Data and methods

2.1. Application design and development

The present study involved the development of an iOS application capable of performing iOS-assisted neurosurgical navigation. To the best of our knowledge, no free and reliable mobile neuronavigation system currently exists that can provide real-time neuronavigation in emergency settings. The innovation of this work lies in producing an iOS application that enables instantaneous patient registration on standard mobile devices (iPhone 12, iPhone 13, or iPad Pro), offering a free neuronavigation platform to assist clinicians with the placement of EVDs without requiring stereotactic immobilization, reference arrays, or fiducials. To evaluate the features available on iOS-powered devices, anonymized patient data were obtained from an open-source repository.[45]

The initial step was to identify the essential components of a computer-assisted navigation procedure. These included: (i) Processing of pre-procedural scans, (ii) real-time detection and tracking of the patient, (iii) object detection and localization of surgical instruments, and (iv) the ability to map both patient anatomy and the surgical device to imaging data (Figure 2). The overarching goal was to achieve real-time, continuous registration with minimal surgeon input. Accordingly, the user interface was designed to reduce manual interaction, creating a seamless experience.[46] The application integrates multiple programming environments: Python (3.10.10, Python Software Foundation, USA) and TensorFlow (2.12.0, Google, USA) for machine learning models, C++ (17.0.0, Apple, USA) and Metal (Metal 3, Apple, USA) for performance optimization, and Swift (5.9.2, Apple, USA) for the iOS application framework. These were unified using the Xcode Integrated Development Environment (15.4.0, Apple, USA) to build and test the app.

2.2. iOS true depth camera

The iOS TrueDepth camera, typically used for the Face ID feature, uses light detection and ranging (LiDAR, a remote sensing method) to capture accurate topographic data. It projects and analyzes thousands of laser points, measuring their reflection time to create a depth map, which is then coupled with an infrared image. These images are processed by Apple's Neural Engine (compatible chips include A11, A12 Bionic, A12X Bionic, A13 Bionic, A14 Bionic, and A15 Bionic) and compared to the enrolled representation.[47] Although Apple does not report the depth accuracy of the iOS True Depth camera, independent sources estimate it to be approximately 2% at a distance of 3 m.[48]

2.3. AI model creation and training

Two models were developed for the critical steps of surgical navigation:

(i). A semantic segmentation model for head CT scans.
(ii). An object detection model to track EVD catheters.

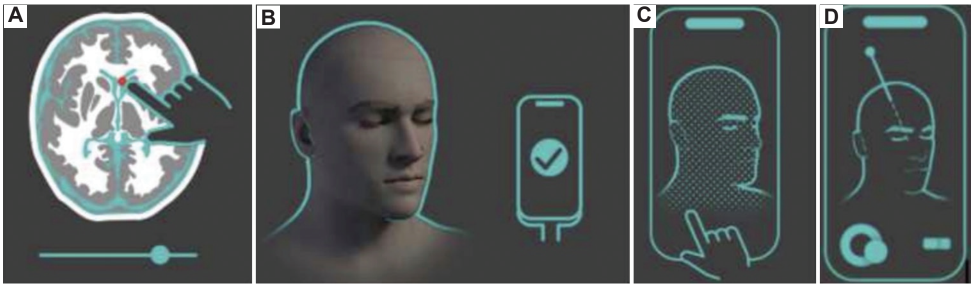

Figure 2. Schematic representation of neuronavigation using an iOS mobile device. (A) Anatomic review and target selection. (B) An iOS device mounted with the patient's head in view. (C) Evaluation of registration parameters. (D) Procedural interface for alignment and depth guidance.

Industrial-strength models, optimized for iOS systems, were rapidly trained using transfer learning. For the head CT segmentation model, the open-source QURE. AI CQ500 dataset was used, consisting of 491 head CTs acquired on multiple scanners.[45] Eight scans were manually annotated to segment key anatomical structures relevant to trauma surgery: background, extracranial soft tissue, skull, brain, and ventricles. These annotations yielded 4,096 CT slices, which were used for model training, validation, and testing, allowing for the identification of each component within an individual CT scan. Our model combines these segmentations with the point cloud generated by iOS devices, fusing point cloud segments with the pre-operative CT scan using GPU acceleration. This fusion process is performed iteratively and then creates the optimal alignment, continuously registering and re-registering during the procedure, as the patient's head is not rigidly secured. The system operates without user input, ensuring instantaneous, continuous neuronavigation and allowing accurate overlay of the EVD catheter location without requiring head fixation or a reference array.

For the EVD object detection model, 937 unique images of EVDs with a visually distinct dodecahedron attachment were acquired in an ICU setting using the front-facing camera of an iOS device to simulate bedside placement. The dodecahedron, attached to the distal end of the EVD, contained a unique QR code on each face to facilitate identification. These images were segmented and used to train a feature-based machine learning algorithm to localize the dodecahedron in space through the iOS device's video feed. The model was externally validated with 200 additional images obtained in non-ICU settings. In total, 700 randomly selected images were used for training and 237 for validation.

Two models were trained: a full network and a transfer-learning model using YOLOv2 (YOLOv2, Ultralytics, USA), both optimized for iOS systems to achieve real-time, accurate navigation of the EVD and its custom dodecahedron attachment.[49] To confirm robustness and guard against overfitting or class imbalance, we performed a randomized 10-fold cross-validation with a 90% train/10% testing split.

2.4. Model performance

Segmentation models were assessed for accuracy in training and validation cohorts. In addition, we evaluated the initial time required for point cloud merging with the patient's anatomy and quantified cumulative error following scaling, alignment, and rotation. Finally, performance metrics included intersection over union (I/U), varied intersection over union (I/U), and inference times of the iOS application during real-time EVD tracking.

3. Results

We developed an application capable of performing all steps of surgical navigation on iOS devices. The application can load and display head CTs in DICOM or NIFTI format. The surgeon selects the target by touching the mobile device's screen, and the device stores that information for the 3D transformations necessary to perform the navigated procedure (Figure 3).

While the surgeon views the scan of interest, segmentation is performed in the background by a UNet CNN trained on the eight 1 mm head CTs. This model achieved 98.3% testing accuracy and 98.2% validation accuracy using a 50/50 test–validation split. To confirm that the model was not overfitting and remained robust against class imbalance, we performed randomized 10-fold cross-validation with a 90% train/10% testing split, yielding an average validation accuracy of 98.3% across folds. Segmentation requires 30 ms per slice on a standard iPhone 12, or approximately 3 s per scan, and provides the data for surface merging (Figure 4).

The surgeon then mounts the phone in front of the patient's head and navigates to the next screen. The video feed semantically segments the largest head in view and captures 3D data from the TrueDepth camera. The application allows the surgeon to inspect the TrueDepth image in 3D to ensure scan adequacy before merging.

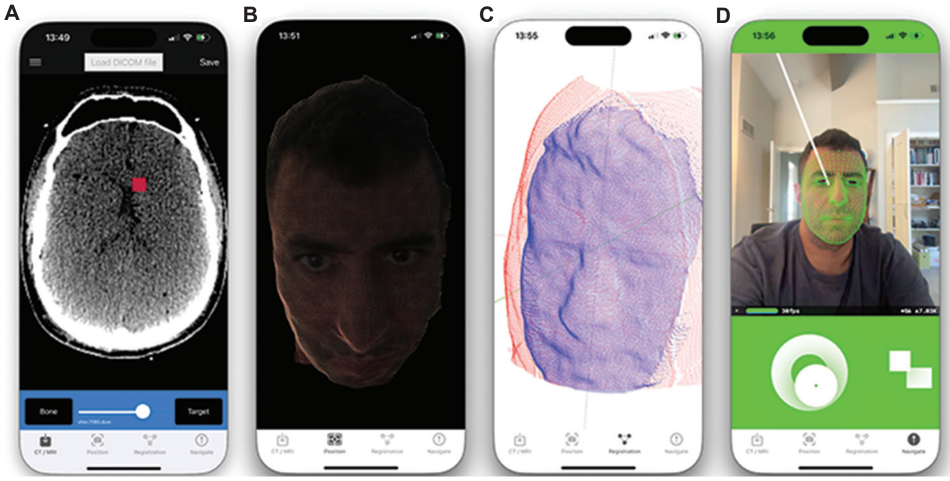

Figure 3. iOS application screenshots during use. (A) DICOM viewer for targeting. (B) Point cloud obtained following device mount. (C) Registration review to inspect the point-cloud merge. (D) Augmented reality-driven navigation interface with alignment and depth guidance.

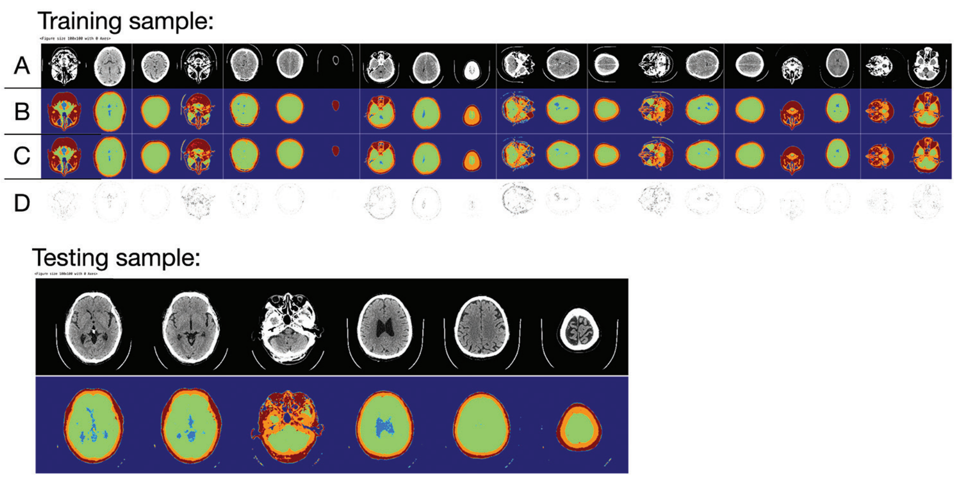

Figure 4. Results of the semantic segmentation model (SSM). Training samples provide four rows of information: (A) original scan, (B) predicted segmentation, (C) ground-truth segmentation, and (D) error map. Testing samples demonstrate performance on previously unseen data. The SSM achieved an accuracy of 98.3% for testing and 98.2% for validation when segmenting background (purple), extracranial soft tissue (red), bone (orange), neural tissue (green), and ventricles (blue).

Once accepted, the phone performs a point-cloud merge by aligning the segmented head CT with the 3D TrueDepth scan. The registration algorithm applies scaling, alignment, and rotation to achieve a coded threshold of $1 \times 10^{-8\,\mathrm{cm}}$ average difference between the two-point clouds (Figure 2). The initial merge requires an average of 3.8 s, after which updates are performed at 60 merges per second in the background, synchronized with the 60-fps display of the navigated screen.

The final navigated display provides the surgeon with an AR view of the patient, a projection of the target trajectory, and an alignment interface for navigating the specialized EVD stylet (Figure 5). Training of the tracking model for 1,000 epochs resulted in an I/U of 1.0 and a varied I/U of 0.98 for the YOLOv2 model, with inference times of 800 μs on Apple's Neural Engine.

4. Discussion

The performance of our AI algorithms, combined with the successful implementation of a functioning application running these models on local hardware, suggests that iOS devices can feasibly provide a complete neurosurgical navigation experience. This innovation has the potential to significantly improve the accessibility, efficiency, and cost-effectiveness of surgical navigation, particularly in resource-limited settings. For example, it could bring navigation directly to the bedside, enhancing accuracy in procedures such as EVD placements, which currently carry error rates of up to 25% with the standard blind, landmark-based

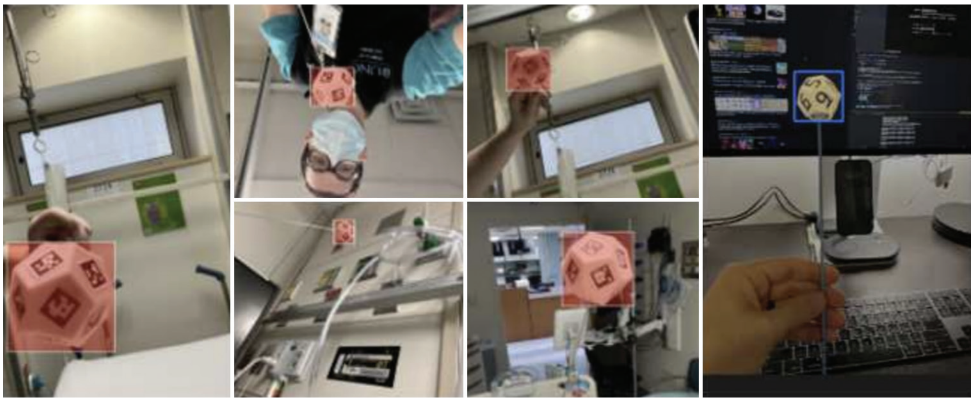

Figure 5. Example of a dodecahedron attached to an external ventricular drain stylet. Sample training data/validation data are shown with red segmentations; testing data are shown with blue bounding boxes. The model successfully tracked and localized the different markings on the dodecahedron.

technique.[41,50] While experienced providers may not require such assistance in straightforward cases, AI-based navigation could improve safety and efficacy for trainees and in patients with challenging anatomy. By improving first-pass accuracy, AI-assisted systems like ours have the potential to significantly reduce downstream complications and associated costs.

Equally important is the role of AI in medical education. Systems equipped with explainable AI features can serve not only as navigational tools but also as digital mentors—offering real-time procedural feedback, recording attempts for later analysis, and integrating with curricula to track skill acquisition longitudinally. This capacity aligns with emerging research on competency-based training frameworks that leverage AI for both assessment and remediation.

Looking ahead, our findings support the argument for more democratized, hardware-agnostic AI integration into surgical care. Unlike legacy stereotactic systems that cost hundreds of thousands of dollars, require sterilized hardware, and demand specialized personnel, our mobile solution operates on a standard smartphone at no additional cost once deployed. This approach not only reduces barriers to implementation in large hospital systems but may also revolutionize emergency neurosurgical interventions in remote or battlefield environments.

A major design goal of this project was to maximize ease of use, accuracy, and portability. By leveraging commercially available iOS hardware, the system enables real-time, continuous patient registration and a full navigation experience without the need for complex, expensive, or proprietary hardware. The integration of AI-based navigational tools into bedside workflows therefore supports not only improved accuracy but also enhanced procedural safety. For instance, misdirected EVD placement can cause parenchymal hemorrhage, intracranial hypertension from occlusion, or delayed CSF drainage—all potentially preventable with better visualization.

Moreover, once adopted, this technology could also serve as a real-time procedural documentation tool. By capturing trajectory data, timestamps, and alignment metrics, the application could offer medico-legal protection for providers and support quality improvement initiatives. It could further contribute to a growing body of procedural analytics that may be mined for insights into improving technique, developing personalized risk profiles, and enabling population-level outcome modeling through federated learning frameworks. In the future, real-time procedural metrics could be incorporated into credentialing, maintenance of certification, and residency milestone assessments.

Although current navigation systems enhance surgical safety, they also have significant limitations. These systems are large and bulky, occupying valuable space in operating or procedural rooms. They often rely on rigidly attached reference arrays that are registered only at the beginning of a case, making them prone to errors if anatomical shifts occur or if the patient's position changes relative to the reference array.[4] In addition, traditional navigation systems require substantial user interaction, which can potentially introduce operator error and inconsistencies during critical steps.[6] In contrast, the automated and standardized nature of this study's custom iOS application minimizes user-dependent variability and enables more consistent, accurate navigation through continuously updated registration of non-immobilized subjects. The iOS application also reduces the need for additional personnel or large, costly equipment, making navigation feasible in bedside and space-constrained settings where it was previously impractical or impossible.

It is important to acknowledge, however, that not all practicing neurosurgeons will adopt or require this technology in their workflow. Surgeons with extensive clinical experience, including hundreds of EVD placements, may find little practical benefit in an additional technological layer. Indeed, the tactile and anatomical intuition developed over decades cannot be easily replaced or replicated by software. This application is therefore not intended to supplant surgical judgment; rather, it is designed to augment procedural safety and education, particularly for trainees, early-career providers, and those who infrequently perform EVD placements.

Trainees often face steep learning curves in ventricular catheterization, a task further complicated by anatomical variability, patient movement, and the urgency of emergent settings. The traditional apprenticeship model, while time-tested, provides variable exposure and feedback. By delivering real-time visual guidance, trajectory alignment, and error detection, AI-based navigation can shorten the time needed to achieve competence, reduce patient risk, and improve trainee confidence. Recent research supports this potential, showing that access to simulation and navigational feedback correlates with faster skill acquisition and lower complication rates in neurosurgical training programs.[51]

Registration remains the key step for mapping a patient's physical anatomy to preprocedural imaging. Conventional systems often rely on as few as 10 points to generate a rigid transformation between real-world and radiographic coordinates.[6] In contrast, our proprietary system leverages the full 30,000 points provided by Apple's TrueDepth camera, corrects for device-specific intrinsic properties, and performs transformations unique to each video frame. This allows anatomy to move relative to the camera while maintaining continuous registration. These operations are accelerated by the on-device GPU,[52] minimizing computational burden on the mobile device. Further study is warranted to quantify the impact on iOS battery performance.

Overall, the use of transfer learning allowed us to leverage pre-trained models developed on large datasets to train our models on relatively small datasets, resulting in high accuracy and robustness. For the head CT segmentation model, we leveraged the well-studied open-source QURE. AI CQ500 dataset, consisting of 491 head CTs obtained on multiple scanners, which improved the generalizability of our model compared to training on institutional CTs alone.[45] The data collection and annotation processes for both models were time-consuming and required expert knowledge. These models further provide opportunities for further iteration and the incorporation of richer datasets, such as MRI, or for segmentation of additional anatomic structures and pathologies (e.g., tumors, vasculature, cranial nerves). With Apple's CoreML architecture, the models are efficiently accelerated, facilitating rapid inferences that drive the app.

The use of AR in neurosurgical navigation offers a more intuitive and immersive experience for the surgeon while minimizing the fatigue often associated with virtual reality solutions.[3] The iOS application utilizes AR to provide real-time visualization of surgical trajectories, anatomic boundaries, and feedback regarding the system's accuracy. These cues may help provide surgeons with an "X-ray vision–" like understanding of patient-specific anatomy, thereby increasing confidence during procedures.

While the present study focused on the feasibility of using an iOS application for navigated EVD placements, there are many potential future applications for this technology. For example, the iOS application could be used for remote surgical guidance, allowing a surgeon in one location to guide another surgeon through a procedure using shared visualization. In addition, it could serve as a training and educational tool, providing a realistic and immersive simulation environment for trainees to practice neurosurgical navigation or to explore anatomy through an alternative medium. The next step will be to compare the application's navigational accuracy against the gold standard of head CT for EVD placement in cadaveric models.

There are several limitations to this study that should be acknowledged. First, this is a proof-of-concept feasibility study. While our model successfully demonstrated that an iOS application can track an EVD in real time, its effect on EVD placement accuracy and clinical outcomes remains unknown. Given the feasibility design, only a limited set of evaluation metrics and parameters were analyzed, which will be expanded in future studies. The next step will involve cadaveric testing to rigorously evaluate the accuracy and safety of the iOS application in a controlled setting. In addition, the small sample size limits the generalizability of findings, underscoring the need for larger studies. Furthermore, the application's overall clinical utility in navigating EVD placement cannot be determined until it is directly compared with the gold standard of head CT, which will be the subject of subsequent research.

Nonetheless, the present study demonstrates the potential of iOS devices to improve neurosurgical navigation, particularly for trainees and inexperienced providers, and establishes a foundation for future research in this area.

5. Conclusion

The goal of this investigation was to integrate existing technologies in registration and object tracking into a single custom application that can perform EVD navigation on an iOS device at the bedside. This approach facilitates navigation by neurosurgical providers without requiring complex setups that delay urgent or emergent patient care. Our data demonstrate that such an endeavor is feasible, with the custom iOS application achieving high accuracy and near-instantaneous results.

The development of a handheld iOS application for neurosurgical navigation represents a promising advancement in the field. Importantly, its greatest value is likely not for seasoned neurosurgeons who routinely perform EVD placements, but for those with less frequent exposure—such as residents, junior faculty, or providers who take call infrequently. By offering real-time, AR-based guidance and objective trajectory verification, the application holds significant potential as both a safety tool and an educational aid.

Although not every surgeon will find it necessary to adopt this system, its role in surgical education and simulation could support the development of procedural competence among lower-volume practitioners. Ultimately, this may enhance patient safety, reduce complications, and lower costs without adding logistical burdens or delaying emergent care. While further research is needed to evaluate its performance against gold standards such as CT in cadaveric and clinical studies, early data suggest that this technology may improve the accessibility and cost-effectiveness of neurosurgical navigation.

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Conflict of interest

The authors declare they have no competing interests.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data are available from the corresponding author upon reasonable request.

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