Novel Technique for the Identification of Hip Implants using Artificial Intelligence

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INTRODUCTION:

The forecasted growth of total hip arthroplasty (THA) over the next decade will necessarily result in an increase in revision THA. A critical aspect of revision surgery is preoperative planning, including identifying current implants to ensure implant-specific tooling for prosthesis extraction. Failing to plan properly may lead to difficulty with implant removal, which may result in increased operative time, blood loss, periprosthetic fracture, and/or other complications further exacerbated by prolonged time under anesthesia. Artificial intelligence (AI) has already shown promise in aiding clinical decision making in medicine at-large, including studies demonstrating the ability to identify hip implants. Limitations of those studies include relatively small datasets, wildly variant stem designs, lack of path forward to scale solutions, and requirement of AI-expertise to design machine learning models. To address those limitations, we developed a novel technique to generate large datasets, tested against radiographically-similar stems, demonstrated ability to scale to any variety of implant, and utilized a no-code machine learning solution.

METHODS:

We trained, validated, and tested an autoML-implemented convolutional neural network to classify 9 radiographically-similar femoral implants, all with a metaphyseal-fitting, wedge taper design. Our technique generated 27,020 images, split into training (22,957) and validation (4,063) sets. We obtained 786 test images from retrospectively-collected patient anterior-posterior (AP) plain radiographs (66.5%) at a single health system, AP radiographs from cadaver labs (28.2%), and journal articles (5.2%). Our novel technique utilizes CT-derived projections of a three-dimensional scanned model of an implant superimposed within a computed tomography (CT) pelvis volume. We used computer-aided design (CAD) modeling to place implants in proper position in 3D-space within the proximal femur of the CT image and then exported that CAD model using a common coordinate system to maintain positioning relative to the CT imaging [Fig. 1]. We used MATLAB to superimpose the CAD model within the CT pelvis volume. The combined CT-implant volume was rotated to a varying degree randomly along the AP (±5 deg), medial-to-lateral (±25 deg), and longitudinal (±25 deg) axes; in addition, the Hounsfield-level corresponding to bone was randomly attenuated to create images of varying bone intensity. The resulting image projections were fed into our machine learning model. Performance of the model was evaluated by calculating the sensitivity, specificity, and accuracy.

RESULTS:

Preliminary results of our machine learning model discriminated the 9 implant models with a mean accuracy of 97.4%, sensitivity of 88.4%, and specificity of 98.5%. [Table 1 & 2]

DISCUSSION AND CONCLUSION:

Our novel technique to develop a hip implant detection model demonstrated the ability to accurately identify among 9 radiographically-similar implants. Furthermore, our technique is easily scalable with the ability to generate large datasets, as well as add historic and/or obscure implants that are not represented in current datasets. Lastly, the no-code machine learning model that we implemented demonstrated the feasibility of obtaining meaningful results without AI-modeling expertise, hopefully encouraging others to further build upon these results.

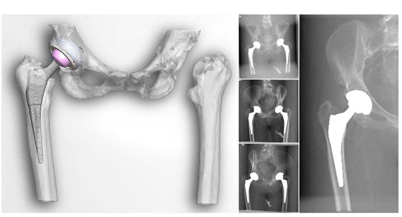

Table 1: Implant Detection Results

Implant	TP	FN	TN	FP	Specificity	Sensitivity	Accuracy	PPV
Accolade 2	34	3	746	3	0.9960	0.9189	0.9924	0.9189
Actis	114	7	664	1	0.9985	0.9421	0.9898	0.9913
AMIS	31	0	743	12	0.9841	1.0000	0.9847	0.7209
Anthology	159	33	589	5	0.9916	0.8281	0.9517	0.9695
Corail	33	3	725	25	0.9667	0.9167	0.9644	0.5690
Echo	111	8	659	8	0.9880	0.9328	0.9796	0.9328
Polarstem	132	21	620	13	0.9795	0.8627	0.9567	0.9103
Taperloc	36	5	729	16	0.9785	0.8780	0.9733	0.6923
Trilock	45	11	722	8	0.9890	0.8036	0.9758	0.8491
Model	695	91	6197	91	0.9855	0.8842	0.9743	0.8842

Table 2: Confusion Matrix

		True/Actual Values								
	Implant	Accolade 2	Actis	AMIS	Anthology	Corail	Echo	Polarstem	Taperloc	Trilock
Predicted Values	Accolade 2	34	0	0	0	0	1	2	0	0
	Actis	0	114	0	0	0	0	0	1	0
	AMIS	2	0	31	2	0	1	7	0	0
	Anthology	0	3	0	159	1	0	0	1	0
	Corail	0	1	0	10	33	3	8	3	0
	Echo	0	0	0	8	0	111	0	0	0
	Polarstem	1	0	0	5	2	3	132	0	2
	Taperloc	0	0	0	7	0	0	0	36	9
	Trilock	0	3	0	1	0	0	4	0	45