MODULAR ARTIFICIAL INTELLIGENCE MODELS FOR BODY COMPOSITION RESEARCH

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Introduction

- Body shape and body composition are comprehensive health indicators and have strong correlations to many diseases and health states[1,2].
- Artificial intelligence (AI) and deep learning are ideal tools for analyzing large sets of high dimensional structural data, like medical images.
- We seek to explore the relationships between 3D body shape and dual energy X-ray absorptiometry (DXA) body composition.
- Large datasets are required for training powerful deep neural networks however, our 3D and DXA dataset is modest.
- We explore a method for training a deep learning model to overcome the data scarcity issue.

Objective

The objective was to train a deep network to learn meaningful information from DXA scans and use the subnetworks for the following task:

1. Predicting three-dimensional (3D) anthropometry from DXA scans
2. Generating analyzable DXA images from 3D body scans.

Methods

Data:

- DXA scans (n = 20,000) were split into a train, validate, and test set

DXA Neural Network Training:

- A variational auto-encoder (VAE)[3], consisting of an encoder and a decoder subnetwork, was trained using a semi-supervised schema.
- Encoder takes the DXA image and learns a meaningful embedding of the image data.
- Decoder takes the embedding and reconstructs the corresponding DXA image

3D Anthropometry Training:

- The trained encoder was further trained on a dataset (n = 1103) to predict 3D anthropocentric measurements from DXA scans.

3D to DXA Training:

- The decoder network was further trained on a data set (n = 1011) to generate DXA scans from 3D body scans

Results

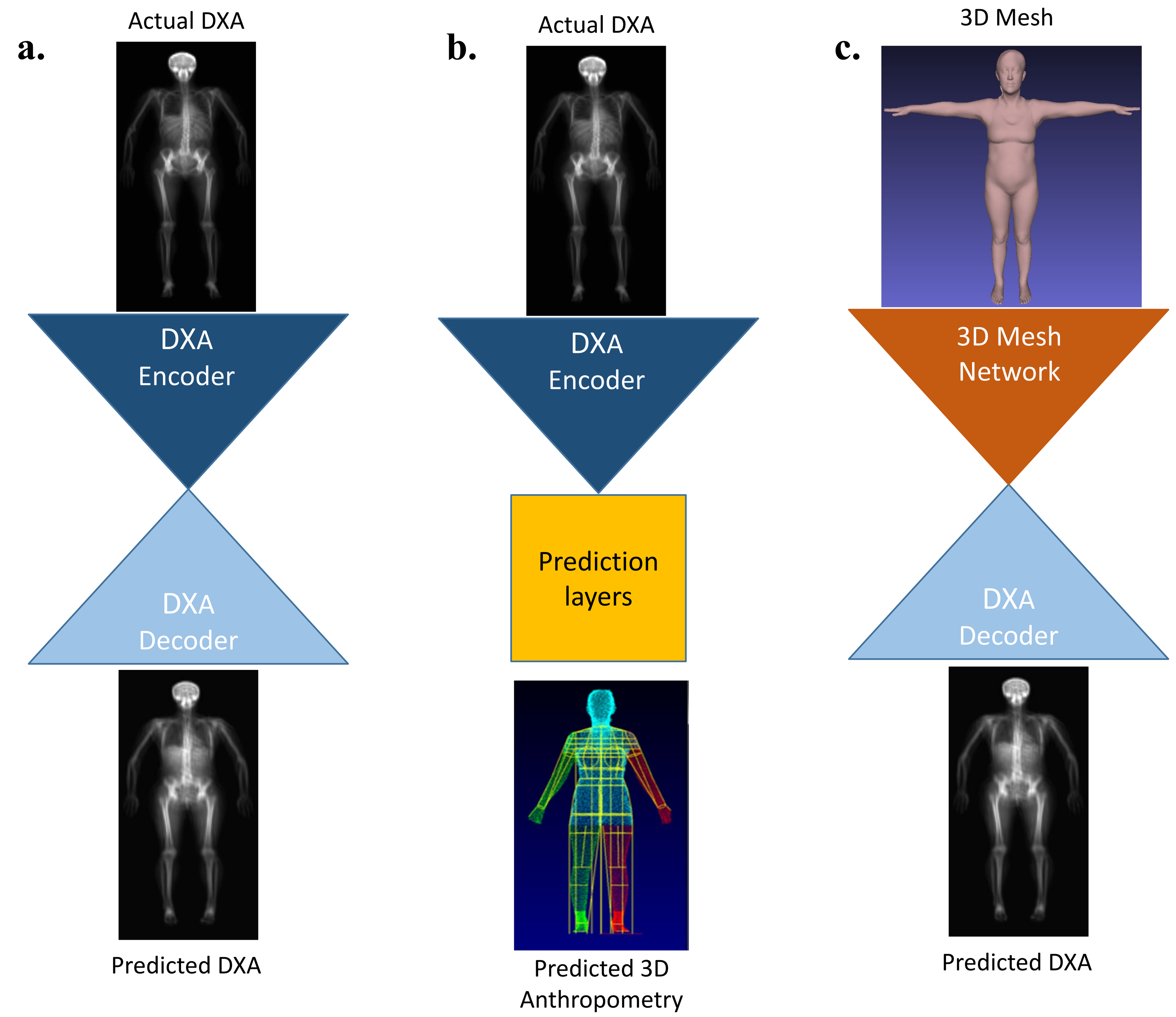

Figure 1. Neural network inputs, outputs, and architecture. a Dual energy X-ray absorptiometry (DXA) images are fed to the variational auto-encoder (VAE). The encoder learns an embedding of the DXA images and the decoder reconstructs the DXA image from the embedding. Training continues while the difference between the actual and predicted DXA decreases. **b** Neuronal layers are appended to the end of the trained DXA encoder and trained to predict 3D anthropometry measurements from DXA images. **c** A 3D mesh neural network is prepended to the trained DXA decoder and trained to generate real DXA scans from 3D body scans or meshes.

Table 1. Coefficient of determination (R^2) root mean squared error (RMSE) comparing neural network prediction and actual 3D anthropometric measurements

Anthropometry	R^2	RMSE
Total Volume	0.96	3.29 mm^2
Torso Volume	0.93	3.17 mm^2
Total Surface Area	0.95	0.05 mm
Chest Circumference	0.92	31.45 mm
Bicep Right Circumference	0.92	1.42 mm
Bicep Left Circumference	0.94	1.13 mm
Hip Circumference	0.92	33.63 mm
Waist Circumference	0.83	50.82 mm
Right Thigh Circumference	0.83	20.17 mm
Left Thigh Circumference	0.81	19.43 mm

Table 2. Peak signal to noise ratio (PSNR) and structural similarity index (SSIM) for predicted DXA scans from 3D meshes

Metric	Mean	STD	Min	Max
PSNR (db)	25.73	2.56	18.74	31.93
SSIM	0.88	0.51	0.68	0.95

Table 3. Coefficient of determination (R^2) root mean squared error (RMSE) comparing actual and predicted DXA composition. Composition was obtained by analyzing actual and predicted DXA scans on clinical commercial DXA analysis software.

DXA Measurement	R^2	RMSE (g)
Total Mass	0.92	5.28
Total Fat	0.66	7.95
Total Lean	0.80	8.94
Total BMC	0.65	0.39

Results (cont.)

DXA Pretraining:

- Our semi-supervised VAE training set up (**Figure 1a**) resulted in two trained subnetworks with good understanding of the DXA image structure.

3D Anthropometry Network:

- Task specific training of the encoder resulted in a neural network (**Figure 1b**) with the ability to accurately predict 3D anthropometry (**Table 1**) from an unseen test set (n = 186) of DXA scans.

3D Mesh to DXA Image Network :

- Using a 3D mesh network[4] with the trained decoder (**Figure 1c**) allowed for the prediction of DXA scan from 3D scan/mesh on an unseen test set (n = 145).
- Acceptable peak signal to noise ratio (PSNR) for 16-bit images above 20 db. Structural similarity index (SSIM) measure image reconstruction quality between 0 and 1 where 1 is a perfect reconstruction[5]. See **Table 2.**
- Analysis of actual and predicted DXA was performed on clinical commercial DXA software to quantify lean and fat soft tissue quantities as well as bone quality (**Table 3**).

Conclusion

- Our training schema allowed us to leverage our large DXA dataset to produce a modular DXA image deep learning model in which the two trained subnetworks can be further trained for task specific problems.
- The described methods are applicable to other data domains and can be useful when training data is scares.

References

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