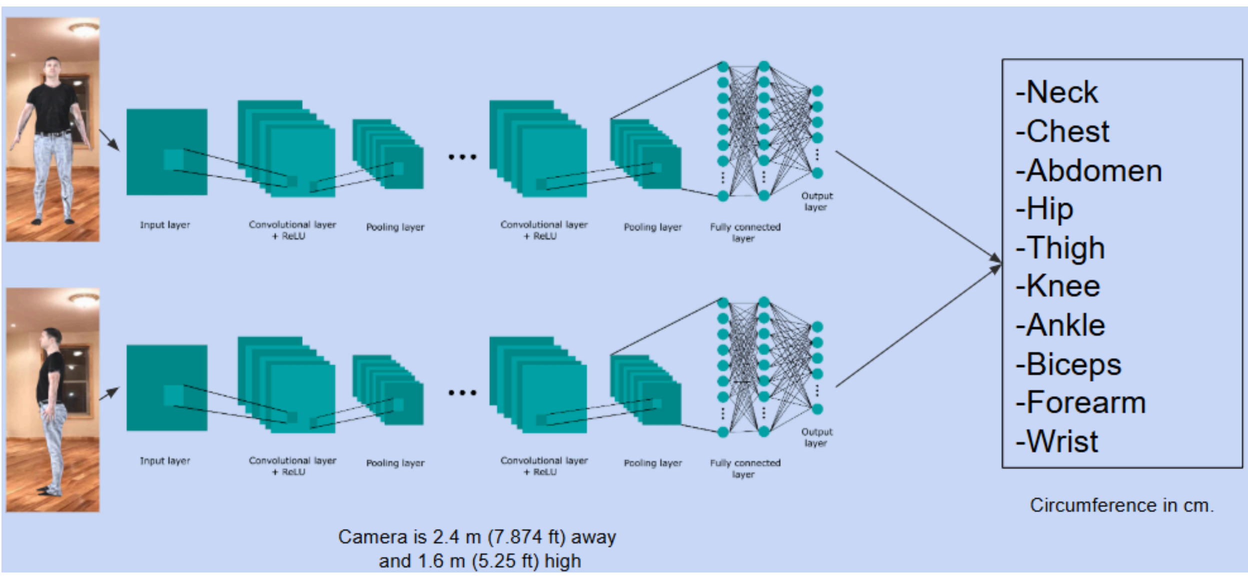
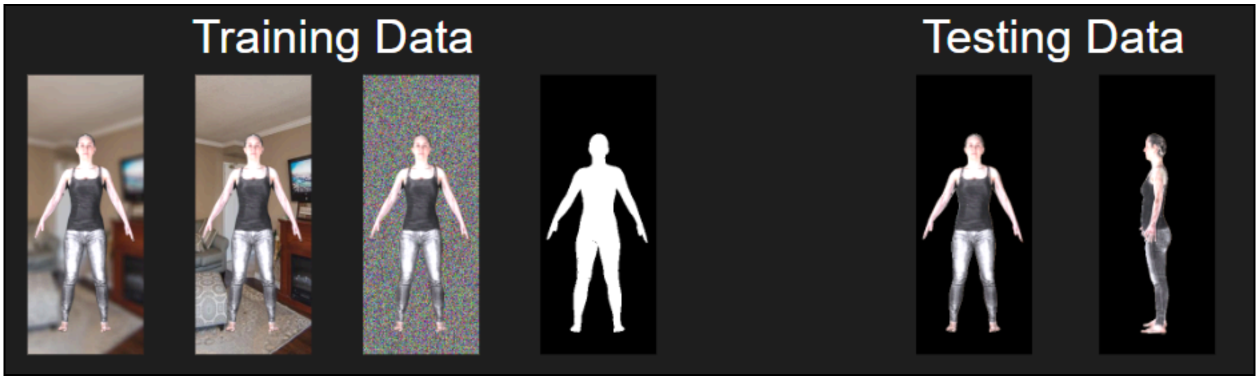
BFNet

Traditional body fat percentage measurers are not generally available to the public. They are typically found at gyms or supplement stores- however, it is common to have to purchase personal training or some supplement product to use these devices. On top of this, these devices are known to be inaccurate! BFNet proposes a solution that is competitive against traditional body fat percentage measuring devices that is accessible to all with a camera.

BFNet is an AI solution composed of 2 models- an image-to-measurement model IMGtoM, and a measurement-to-bodyfat model MtoBF.



IMGtoM takes as input 2 images of a person holding an A-pose, one from the front and one from the side. These images are taken from a camera positioned approximately 7 feet 9 inches away, and 5 feet 3 inches high. Each of these images is then passed into an EfficientNetB5 network, which has already been pre trained on image data. The last layers of each of these networks are then concatenated and passed into a hidden layer with 128 parameters, and l2 regularization with 0.01 strength. These parameters were identified as optimal through subsequent training of the model.

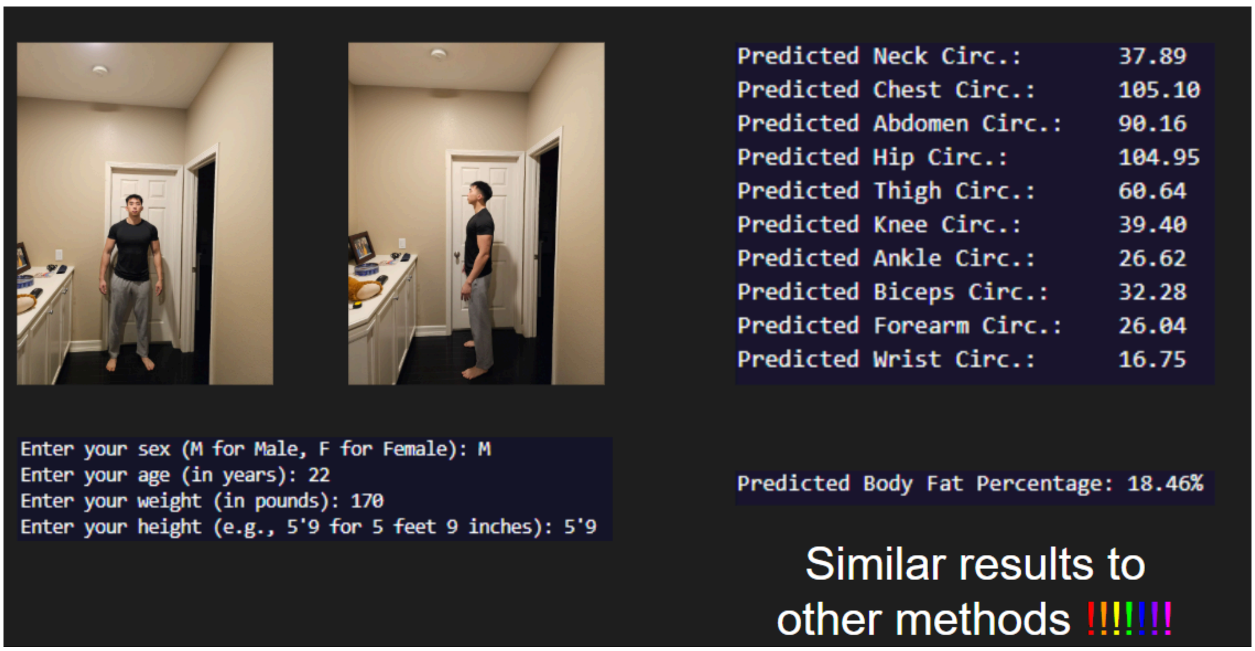


During the training process, the layers of the EfficientNetB5 models were frozen - we are only training the hidden layer with the concatenated last layers of the EfficientNetB5 models. We then compare each output to each circumference measurement (in cm) associated with the image. These measurements consist of neck, chest, abdomen, hip, thigh, knee, ankle, biceps, forearm, and wrist, and were chosen because they matched the dataset that learns a bodyfat % from said measurements. **This means that there are actually 10 IMGtoM models,** one for each measurement. The mean squared error loss is then back propagated through each network for each of their measurements. Images with a blurry, clear, noisy background and silhouettes (left to right) were used for training, while images without a background were used for testing. This was done to ensure that the background did not lead to any variance in values. The data from [Body-fit and Body-rgb (NOMO-3d-4K-scans)](), associated with the *Silhouette Body Measurement Benchmarks* by Yan et al, consists of roughly 22,000 pairs of front and side images of women and men, as well as their corresponding body measurements. These data points include varying backgrounds (factored into the 22,000), and through splitting the data as mentioned above we roughly achieve an 80/20 data split. The training data was placed in another 80/20 data split to obtain the training dataset and the validation dataset. To include more variance in the data, and ensure that the model was able to accurately observe each measurement, we included transformations such as 180° rotation, horizontal shifting by 10%, and vertical shifting by 10% on the training data. The mean average error, in centimeters, of each model is listed below:

Average error per model (cm)

Neck:	3.8	Knee:	2.2
Chest:	8.0	Ankle:	2.1
Abdomen:	9.8	Biceps:	2.8
Hip:	5.6	Forearm:	2.1
Thigh:	4.2	Wrist:	1.1

The second model, MtoBF, is trained on roughly 400 points of data which include a person's neck, chest, abdomen, hip, thigh, knee, ankle, biceps, forearm, and wrist circumference in centimeters, as well as the person's age, weight, sex, and height. This dataset was found from [Body Fat Extended Dataset](). During testing, the age, weight, sex, and height measurements are manually inputted, as they should be known by the individual, and hence have no need for prediction. This data was modeled using a linear ridge regression model with an alpha value of 1.0. The model was chosen through 10-fold cross validation across multiple models, and the alpha value was determined through grid search. Through CV, we were able to determine that the model had a mean average error of 3.27% body fat across these 400 data points.



During testing of BFnet (in main.py), an individual must put a front and side photo of themselves holding an A-pose with the camera approximately 7 feet 9 inches away from themselves, and the camera 5 feet 3 inches tall. These images should go in the 'Test' folder and be labeled 'test_front.jpg' and 'test_side.jpg' respectively. The individual will then be asked to input their sex, age, weight, and height. The weights of the 10 IMGtoM models and MtoBF model are then loaded in, and the data is passed through to predict a bodyfat %. After testing this on myself, BFNet predicted that I was 18.46% bodyfat. Although I cannot verify its accuracy, traditional handheld predictors have estimated that my bodyfat was similarly around 18%. This means (at least for me) that BFNet is competitive with traditional bodyfat predictors.

There were 2 main sources of error identifiable in BFNet. First, the not all predictors in the MtoBF dataset were predictions in the IMGtoM dataset. For instance, the IMGtoM dataset did not explicitly predict an 'abdomen' circumference, so for males, the 'max waist' measurement was used, and for females the 'natural waist' measurement is used. Similarly, images of men had an explicit 'chest' measurement, but for images of women this was not available, and a ‘bust’ circumference was used. Lastly, there were no ‘forearm’ or forearm related measurements whatsoever, so for both men and women we used the ‘elbow’ circumference measurement.

The second main source of error is the fixed camera position. In practice, it is difficult to enforce a set camera distance and height. At different heights and lengths, the measurements may be larger or smaller than what they should be, and this error would be propagated throughout the model. Although there is no way to fix this for BFNet currently, my next project will be inspired from this project and will use computer vision to accurately predict the camera’s distance and height relative to an individual in real time. If there were to be any substantial improvements to BFNet, it would be to incorporate the future project back into BFNet for pinpoint accuracy.

Referenced Works

1. S. Yan, J. Wirta and J. -K. Kämäräinen, "Silhouette Body Measurement Benchmarks," 2020 25th International Conference on Pattern Recognition (ICPR), 2021, pp. 7804-7809, doi: 10.1109/ICPR48806.2021.9412708.

2. N, Ruiz, M. Bueno, T. Bolkart, A. Arora, M. Lin, J. Romero, R. Bala, “Human body measurement estimation with adversarial augmentation,” International Conference on 3D Vision 2022. https://www.amazon.science/publications/human-body-measurement-estimation-with-adversarial-augmentation