STYKU PHOENIX: PREDICTING DEXA BODY COMPOSITION USING 3D FULL BODY INFRARED SCANNING

By Raj Sareen, BSc, MSc Physics

Background

We demonstrate a strong association and correlation between body composition and precise anthropometrics, as measured by our 3D body scanner. Our work is fueled by two important considerations: (1) Body Composition analysis, or the study of the amount and distribution of fat, lean-muscle, and bone mass throughout the human body, has proven to be a very useful screening tool in the health, wellness, and fitness sectors. Extensive studies have shown the risks of all-cause mortality are significantly correlated with body composition (as well as waist-to-hip ratio) [1]. And with the significant rise of obesity throughout the world, there is a pressing need to develop more science and technology to assess and improve human health. The other consideration and inspiration is (2) the lack of an inexpensive, non-invasive, highly precise and accurate device to measure or even predict fat mass and other basic body composition parameters. Measuring body composition accurately and reliably has proven to be challenging outside the laboratory. To start with, only a few imaging devices exist that actually see fat. Namely, they are Magnetic Resonance Imaging (MRI) and Computerized Tomography (CT). Both of these devices are impractical for commercial use. Outside of imaging, the only manual method for measuring fat is via a dissection of a cadaver, a common method and considered a ground truth in early work.

As a result of the technological limitations and practical costs associated with measuring body composition, prediction models have been employed by various other methods. Examples historically include hydrostatic weighing (1960-1970), skinfold calipers and tape measures (1980's), and more recently Bioimpedance devices (in 2000's, e.g. Inbody, Tanita, and Omron). For the most part, these prediction models have been useful in education, but have had tremendous shortcomings in precision and accuracy. There use seems to fuel a continuous contentions debate about what is considered an accurate assessment within non-medical and non-scientific sectors. As a result, outdated metrics such as BMI and mis-leading scales are widely used and grossly misrepresent the state of health of many.

Besides having a great need for increased awareness and education of modern methods, and standards, there is a also a vast opportunity to commercially disrupt this market with better technology.Given the advent of new 3D depth sensors and their ability to map the surface of the body, precise anthropometrics is now possible and holds tremendous promise. The aim of our work here is to show that precise anthropometrics via 3D body scanning by Styku, as opposed to the imprecise instruments such as skin-fold calipers and tape measures, yield excellent correlations with body composition parameters, with the added benefit of being non-invasive, cost-effective, and easy to use. Therefore, we see a path wherein the global wellness economy will move to adopt these new methods quickly in order to reliably predict fat mass, bone mass, and lean mass. And we hope to be a major driver of that effort through our work.

Introduction

Within the global wellness economy, methods such as skin-fold calipers, and hydrostatic weighing are quite common. However, extensive scientific work has shown that these methods significantly underestimate fat. The result is due to poor instrumentation in part, but mainly due to the common use of the Siri or Brozek equations [2]. These relationships have been shown to significantly underestimate fat due to their assumptions about the density of lean muscle and bone mass.

Bioimpedance, a recent method has promised more accurate and reliable results and has gained tremendous popularity commercially throughout the global wellness economy. Although the method is well validated in laboratories and in research settings, studies have shown time and again that the method is highly unreliable in clinical and commercial settings due to its reliance on hydration. As a result, the method has failed to capture the credibility of research scientists [2].

A more practical choice today is DEXA, considered the gold standard for measuring bone density. By measuring bone density explicitly, more accurate mathematical models can be used to predict fat and lean mass and is well validated in the literature [3]. Research scientists have confirmed the accuracy of this method by comparing its results with 4-compartment model (4C Model), the gold standard for total body composition [4] (The 4C Model utilizes various devices to measure explicitly each component of the body)

Although DEXA is the most trusted standard today, challenges do exist. Random errors can be introduced if the subject does not stay still. Systematic differences between various manufacturers can be as high as 4% body fat. Additional errors can be introduced based on the level of hydration in the body. But these errors are small in comparison to some of the other methods used today. And as a result, for the purposes of this study, we chose to use the DEXA method as our criterion method to develop our model.

The real challenge with DEXA is the (1) the increased cost of administration (state laws vary around administering x-ray scans), (2) size of the machine, (3) cost of the machine (can reach the six figures), and time (5-10 minutes for testing). These obstacles make it a difficult solution to adopt globally. As a result, it is very attractive to search for a method that is well can overcome these challenges. We demonstrate that 3D full body scanning in infrared (hereby 3D body scanner) is a very promising alternative.

It helps to point out that the correlations between anthropometrics and body composition is already well known. There is rich body of work by the US Navy and Jackson et. al demonstrating strong relationships with body composition. In fact, the US Navy demonstrated high coefficients of correlations between circumference measurements (with a tape measure) and body composition in their landmark studies in 1984 [8] [9]. And research by Jackson et, al [5] [6] [7] showed strong correlations with body density via regression analysis of skinfold measurements using calipers, which prompted wellness professionals globally to quickly adopt it as a cheap, and easy-to-use standard.

The problem is that this prior instrumentation in anthropometrics required a highly trained technician to visually identify landmarks and take reliable measurements. Because of the cost of training, the difficulty in training, and the natural human error in manual instruments, these tools consistently yield unreliable results in a clinical or commercial setting. As a result, anthropometric methods are rarely used and trusted by professionals, with the lack of any significant improvements in anthropometric instruments coming until now. The advent of inexpensive 3D depth sensors, brings the ability to map the entire surface of the human body with 2mm precision. Highly precise tools such as 3D body scanners could unlock incredible research opportunities in the area of anthropometry. Namely, we've shown that indeed one can determine basic body composition parameters reliably better than using manual anthropometric methods. And we believe there are even more opportunities to disrupt the modern field of body composition analysis with these new tools.

Commercially, it's also worth noting the practical advantages of body scanners, compared with other methods. Body scanners operate in the near-infrared part of the spectrum, and therefore do not penetrate the skin. Non-invasive techniques like body scanning don't require FDA approval unlike DEXA which in many states require a licensed administrator. Therefore, these devices are more practical investments for commercial use as well. 3D body scanners typically have smaller footprints than DEXA, and the assessment process is considerably faster (~30 seconds). With these and many more advantages, we believe this new anthropometric method could become the new gold standard method for body composition prediction and analysis.

Abstract

We've developed an accurate and reliable prediction model (with correlation coefficients for fat mass of 0.94 for women and 0.92 for men) for body composition using anthropometrics measured by Styku's 3D body scanner. Our prediction model is built via regression analysis between automated anthropometrics (circumferences, areas, and volumes in key regions of the body) measured by Styku and body composition, via DEXA, our criterion device. We worked with data collected by the Pennington Biomedical Research Center (PBRC), Louisiana State University. Further regression analysis resulted in strong correlations with Lean Mass, Bone Mass, Android Fat Mass, Gynoid Fat Mass, Visceral Adipose Tissue, and Subcutaneous Adipose Tissue.

PBRC collection of data was funded by a grant from the National Institute of Health (NIH) to study the correlation between 3D infrared imaging and criterion methods for body composition and has published early results. The data for both these devices were stripped of personal identifiable information and then shared with Styku. Once a significant sample size of participants were scanned, Styku began its analysis to explore whether it could predict body fat, lean mass, bone mass, and more using anthropometrics. The methods used to reduce this data and analyze it, and the results of the regression analysis for various components of body composition are presented in this paper with the aim to commercialize the results, build validation in the statistical significance of Styku's body composition prediction models, as well as illustrate the vast potential in further study to explore the prediction power of anthropometrics in the study of human health, fitness, and wellness.

Method

A total of 285 subjects were scanned anonymously on a DEXA (Manufacturer: Hologic, Model: Discovery) and on a 3D Body Scanner (Manufacturer: Styku, Model: S100). Styku uses a Kinect v2 Infrared Camera, which is one of the few 3D depth cameras in the market that produces high resolution depth images. Data was captured between Dec 2016 and March 2018 at the PBRC. The DEXA data was shared with Styku and inspected for recording or measurement errors. The process of inspection included evaluating the integrity of the data collected. 16 of those samples were removed due to recording errors. Samples were either missing gender and/or age data, had the wrong gender recorded, or had erroneous height and/or weight data. Further evaluation was performed on the the raw depth images, RGB images (Styku's 3D body scanner includes an RGB camera that takes 1 image of each subject body, blocking out their head with a black box to keep them anonymous), and the 3D mesh. An additional 23 samples were not used for the following reasons: (1) A Styku software failure in extracting all 200+ body circumferences, areas, and or volumes in scans. These were likely the result of a failure to properly identify anthropometric landmarks in children, which represented a small proportion of the subjects scanned. As a result, 19 of the 23 cases involved one or more missing measurements. We required a full set of anthropometrics for analysis, so samples with missing measurements were removed from the study. Additionally, 2 of the 23 samples removed were found to have the Tower/Camera misaligned. A misalignment of the tower results in systematic biases in the body measurements. Finally, another 2 of the 23 samples removed had issues with clothing. One subject was wearing loose fitting clothing, while another was only partially wearing a compression short.

The remaining number of samples were a set 246 subjects. This sample set was composed of 143 female subjects and 103 male subjects. All 246 subjects were used in the analysis. See Table 1 for the mean and standard deviations for various key parameters in the sample set.

Table 1 - Sample Set

Gender	Samples	Mean and Standard Deviation of Key Parameters						
		Age	Height	Weight	BMI	BFP	Waist	Hip
Female	143	42.3 yrs +/- 19.2	63.4 in. +/- 3.0	154.0 lbs. +/- 35.8	26.9 +/- 5.9	37.3 % +/- 7.2	37.4 in. +/- 5.1	40.9 in. +/- 4.7
Male	103	38.7 yrs +/- 19.5	68.9 in +/- 4.2	192.6 lbs. +/- 48.8	28.4 +/- 6.2	27.2 % +/- 7.8	37.6 in. +/- 5.9	40.3 in. +/- 4.5

Our hypothesis is that anthropometrics should be well correlated with various body composition components. We ran several experiments successively iterating through various anthropometric measurements, measured by Styku and body composition components, measured by Hologic's DEXA. To identify which anthropometrics correlated best with body composition, we ran linear regression on each parameter, one by one. Through trial and error, we arrived at several key anthropometric sites that yielded the highest correlation coefficient. In all cases, we explored age and height dependence, as well as evaluating combinations of measurements to improve the correlation.

Results

Using regression analysis, we found several correlations between various anthropometrics with fat mass, bone mass, lean mass, gynoid fat mass, android fat mass, visceral adipose tissue, and subcutaneous adipose tissue. Using the output of the regression analysis, we built a predictive model for each of the below body composition components. Since that model is part of Styku's intellectual property, the exact anthropometrics used and the formulas that make up the prediction model is not published here and will likely remain a trade secret. However, the coefficients of correlation and standard errors are published here for preliminary validation. Coefficients of correlation (R^2) range from 0.64-0.96. Table 2 lists the coefficients of correlation and standard errors for all body composition components predicted.

Table 2 - Correlation Coefficients and Standard Error for Model

Metric (in lbs)	Age	Female			Male		
		Multiple R	R^2	Standard Error	Multiple R	R^2	Standard Error
Fat Mass	<20 yrs	0.96	0.93	4.8	0.98	0.96	5.6
Fat Mass	>= 20 yrs	0.97	0.93	6.1	0.95	0.91	7.1
Lean Mass	All	0.95	0.91	9.3	0.92	0.84	6.3

Bone Mass	All	0.80	0.64	0.50	0.84	0.70	0.74
Android Fat Mass	All	0.95	0.90	0.79	0.95	0.90	0.94
Gynoid Fat Mass	All	0.96	0.92	1.12	0.97	0.95	1.21
VAT Fat Mass	All	0.87	0.76	0.34	0.90	0.81	0.29
SAT Fat Mass	All	0.92	0.84	0.58	0.92	0.84	0.67

To better visualize the correlations between the Styku's prediction model and DEXA's body composition output, we've included several plots below.

Figure 1 and 2 - Styku vs. DEXA - Body Fat Mass

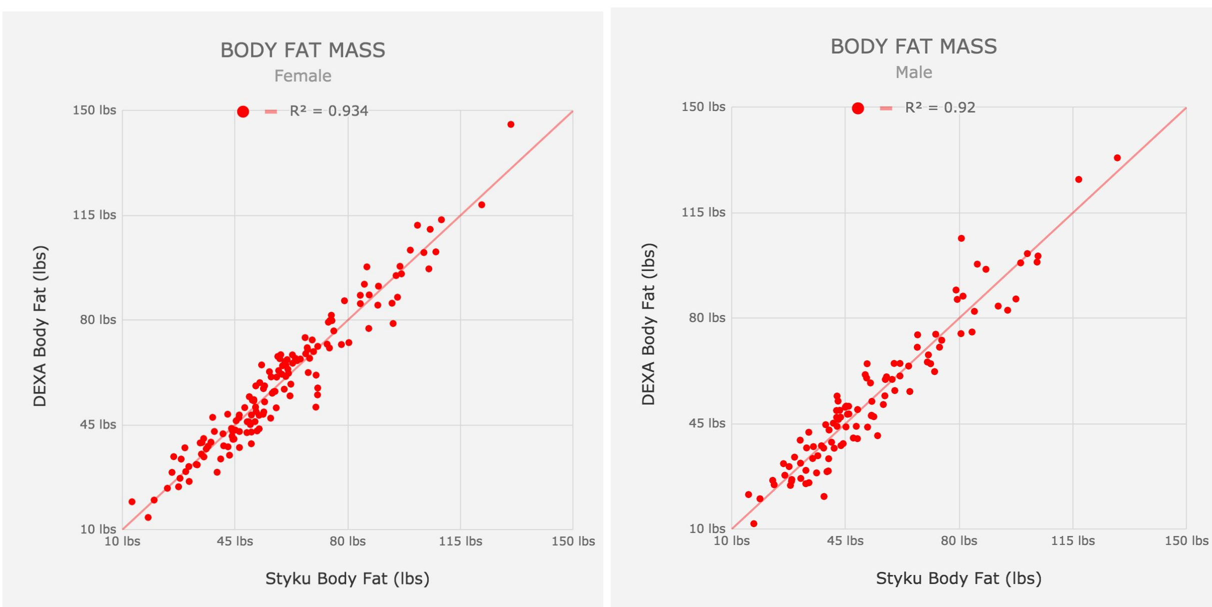


Figure 3 and 4 - Styku vs. DEXA - Bone Mineral Content

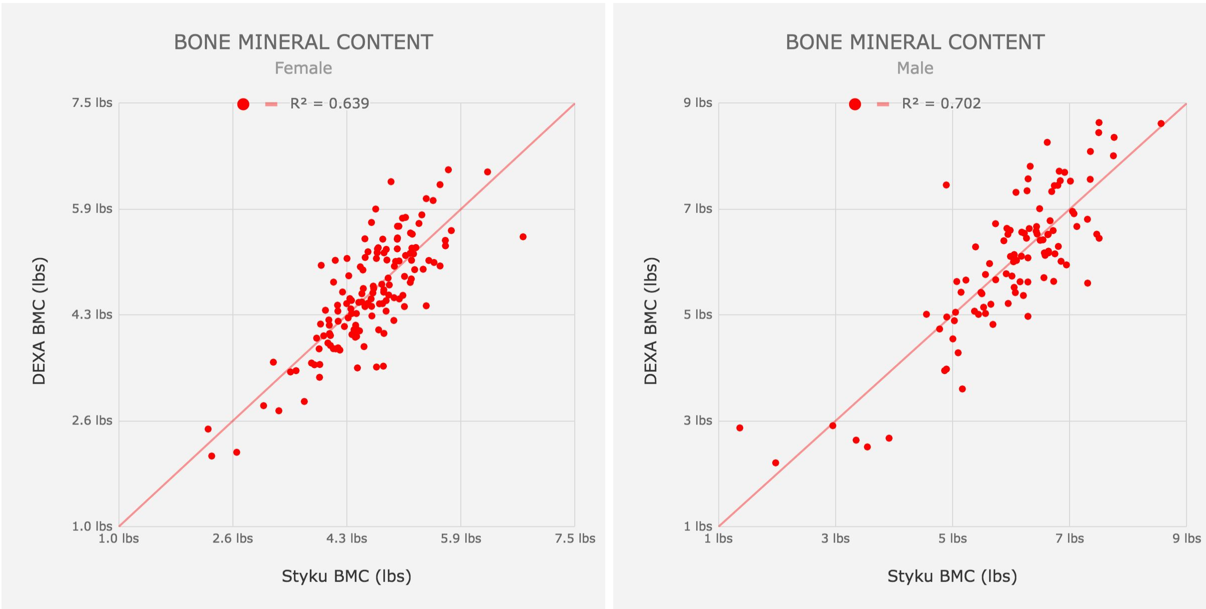


Figure 5 and 6 - Styku vs. DEXA - Android Fat Mass

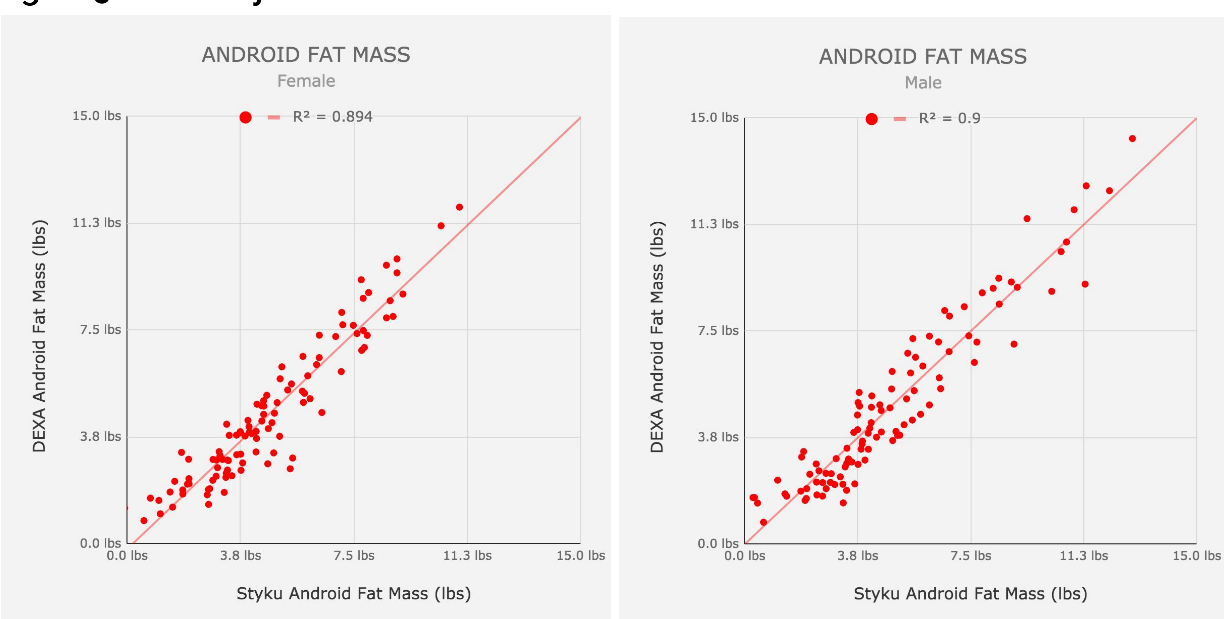
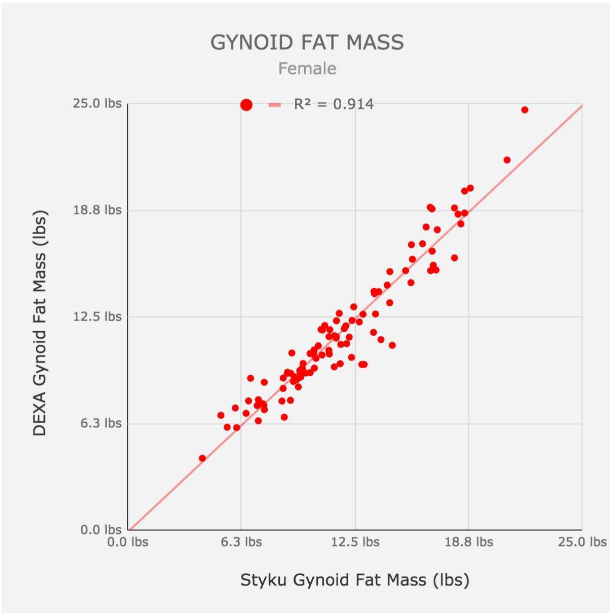


Figure 7 and 8 - Styku vs. DEXA - Gynoid Fat Mass



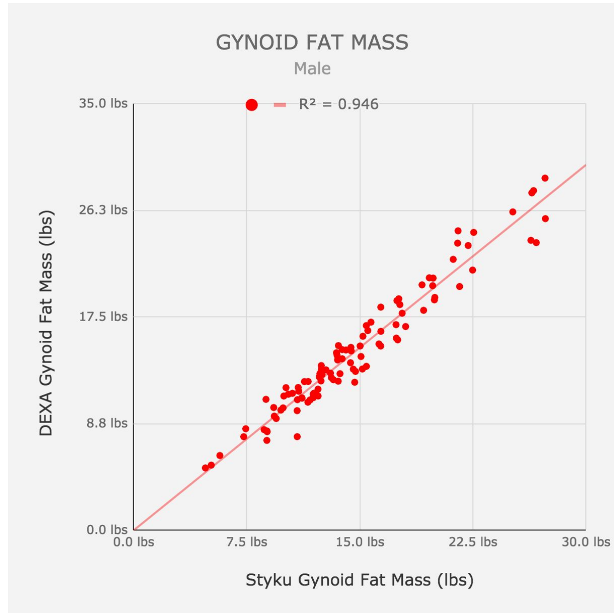
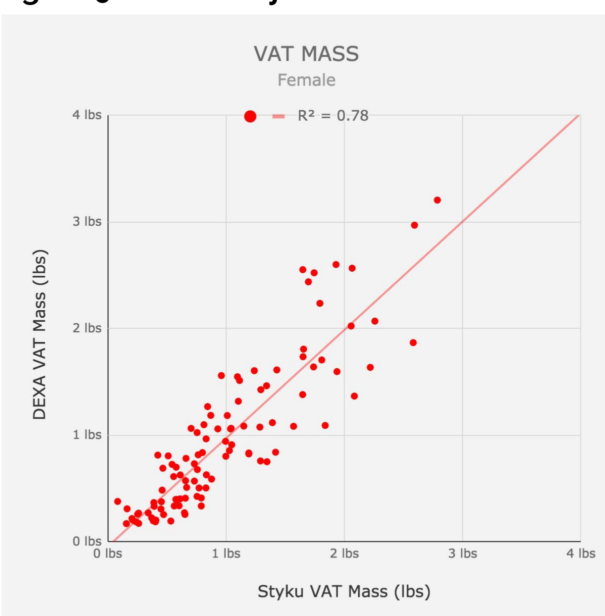


Figure 9 and 10 - Styku vs. DEXA - VAT Mass



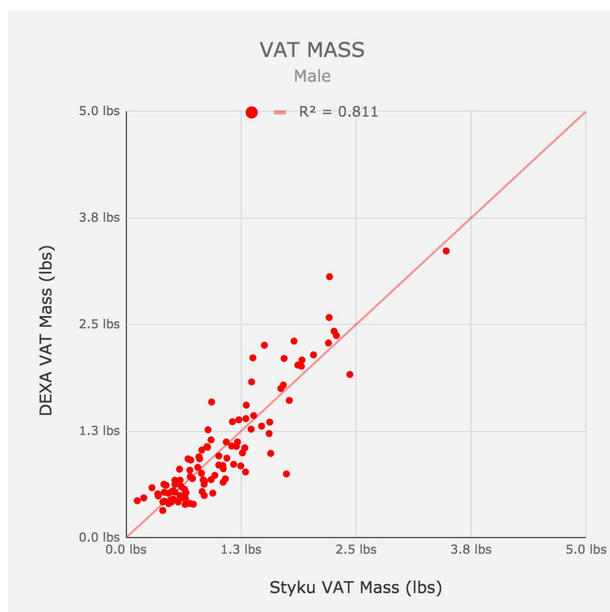


Figure 11 and 12 - Styku vs. DEXA - SAT Mass

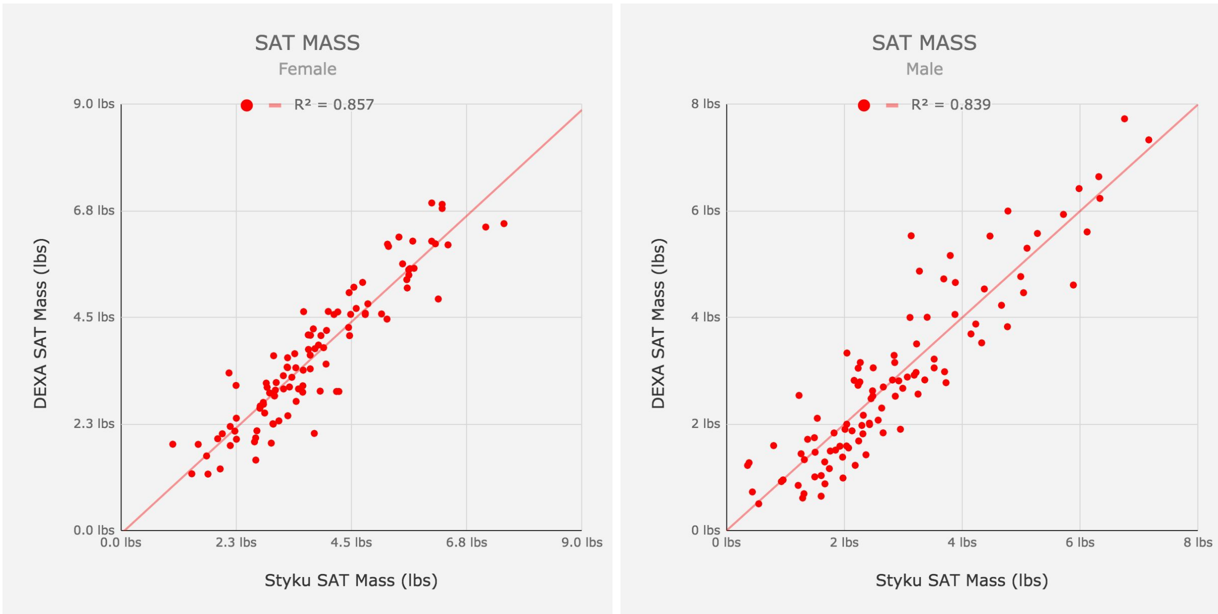
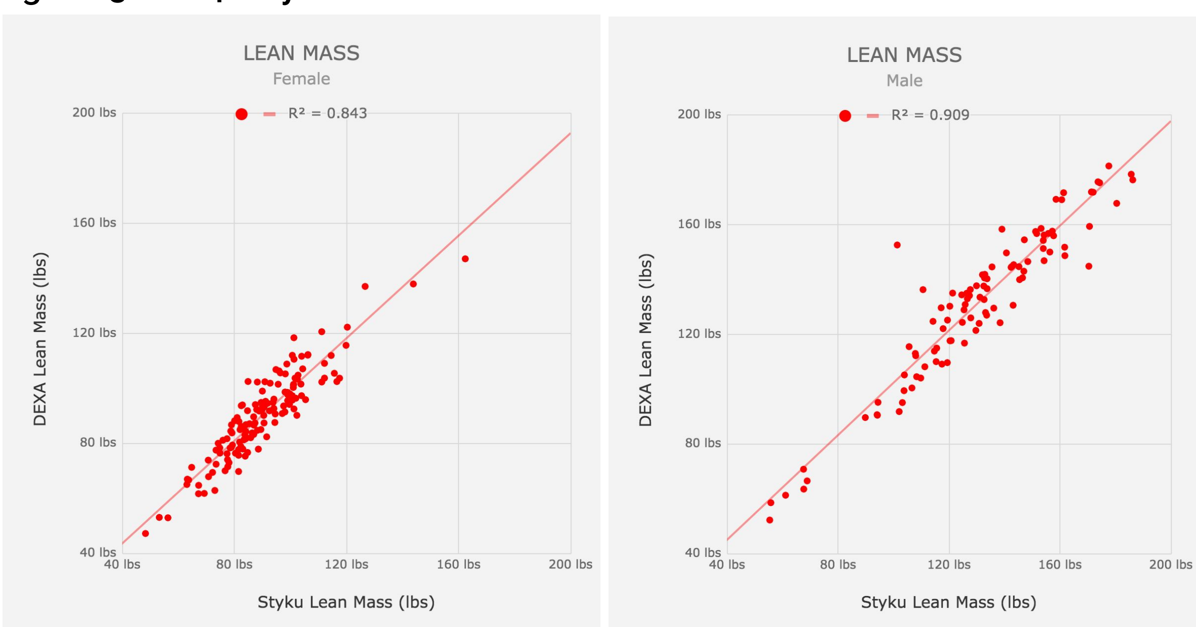


Figure 13 and 14 - Styku vs. DEXA - Lean Mass



Discussion

Preliminary results of Styku's prediction model demonstrates very good prediction quality for most body composition component. The strong agreement with DEXA data suggests anthropometric via 3D body scanning is an attractive method clinically and commercially for providing accurate body composition screening. Further validation is required and future work will likely include cross validation within the same dataset. Moreover, further data collection could yield more age specific models with better correlations, thereby improving the accuracy of the prediction model.

Acknowledgments

The derivation of our model would not be possible without a collaboration, with research scientists at the Diabetes Research Center, mainly Steven Heymsfield, M.D. (Pennington Biomedical Research Center, Louisiana State University), who performed all the data collection. A special thanks to Diana Thomas, PhD, F.O.T.S, at the United States Military Academy (WestPoint), who advised us on the correct data analysis techniques. To learn more about Styku, please visit www.styku.com or reach out at raj.sareen@styku.com

References

1. Bin Dong, Yang Peng, Zhiqiang Wang, Odewumi Adegbija, et. al., Joint association between body fat and its distribution with all-cause mortality: A data linkage cohort study based on NHANES (1988-2011)
2. Magnus Borga, Janne West, et al, Advanced body composition assessment: from body mass index to body composition profiling, Journal of Investigative Medicine
3. Prior BM , Cureton KJ , Modlesky CM , et al . In vivo validation of whole body composition estimates from dual-energy X-ray absorptiometry. J Appl Physiol 1997;83:623–30
4. Heymsfield SB, Lichtman S, Baumgartner RN, Wang J, Kamen Y, Aliprantis A, et al. Body composition of humans: comparison of two improved four-compartment models that differ in expense, technical complexity, and radiation exposure. The American journal of clinical nutrition. 1990; 52:52–8. [PubMed: 2360552]
5. Jackson AS, Pollock ML. Generalized equations for predicting body density of men. Br J Nutr. 1978;40:497–504. [PubMed]
6. Jackson AS, Pollock ML, Ward A. Generalized equations for predicting body density of women. Med Sci Sports Exerc. 1980;12:175–181. [PubMed]
7. Jackson AS, Pollock ML. Practical assessment of body composition. Phys Sportsmed. 1985;13:76–90. [PubMed]
8. Hodgdon, J A ; Beckett, M B, Prediction of Percent Body Fat for U.S. Navy Men from Body Circumferences and Height, ADA143890, NAVAL HEALTH RESEARCH CENTER SAN DIEGO CA, Jun 1984

9. A. Hodgdon, James & B. Beckett, Marcie. (1984). Prediction of Percent Body Fat for U.S. Navy Women from Body Circumferences and Height. 30.