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Body Mass Index Inference using Facial Features and Machine Learning Algorithms

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ABSTRACT: This study aimed to identify whether an exploration party's body-mass indicator (BMI) can be rightly linked from their facial image (snap) in order to ameliorate data landing in dispersion and perpetration exploration. Facial BMI (fBMI) was measured using an algorithm formulated to identify points on each enrolled party's face from a snap. Once facial milestones were detected, distances and rates between them were reckoned to characterize facial fattiness. A retrogression function was also used to represent the relationship between facial measures and BMI values to also calculate fBMI from each print image. contemporaneously, BMI was physically measured (mBMI) by trained experimenters, calculated as weight in kilograms divided by height in measures squared (adult BMI). Correlation analysis of fBMI to mBMI ($n = 1210$) showed significant correlation between fBMI and BMIs in normal and fat orders ($p < 0.0001$). farther analysis indicated fBMI to be less accurate in light and fat actors. Matched brace data for each individual indicated that fBMI linked party BMI a normal of 0.4212 lower than mBMI ($p < 0.0007$). Contingency table analysis set up 109 actors in the 'fat' order of mBMI were deposited into a lower order for fBMI. Facial imagery is a feasible measure for dispersion of mortal exploration; still, farther testing to acclimatize fBMI measures for light and fat individualities are necessary.

KEYWORDS: Body Mass Index (BMI), Facial recognition, ML algorithms.

I. INTRODUCTION

Body Mass Index (BMI) is a well-employed measure to generally describe weight status (1) grounded on the rate between an existent's height and weight. It's used to eventually classify an individual as light, normal weight, fat, or fat (2). Within dispersion and perpetration exploration in particular, measuring BMI can be a handicap that interferes with carrying outgrowth data. First, reaching actors to physically measure BMI is doubtful when aiming to circulate a program nationally due to limited time available and the coffers demanded by facilitators to directly measure weight and height (an exploration quality stadiometer and scales) as well as carrying out the intervention (3). Further, counting on individualities to perform tone-measures may not be realistic or dependable, and measures would frequently calculate on corrective equations (4,5). nonetheless, tone-reported measures are generally used as a secondary measure when physical measures are not doable (6). former exploration has shown that actors tend to overrate their height and underrate their weight, performing in inaccurate BMI data (7). Pursey teal. set up that youthful grown-ups tended to overrate their height while undervaluing weight (6). analogous findings from the National Health and Nutrition Examination Survey (NHANES) and the National Institutes of Health (NHI) data set up youngish (18 – 42 times) and aged (> 55 times old) grown-ups incorrectly reported BMI, with over-reported height and under-reported weight (8). A result to this problem may be the application of party facial photos to assess BMI. With moment's ever-evolving technology, 'selfies', iPhone facial recognition, and social media spots enable druggies to fluently take and display tone-pictures. lately, life insurance companies have begun offering the option of transferring in a selfie to assess health and weight status for eligibility (9).

When performing studies among a population that has grown up in a technology-grounded atmosphere, similar as current council scholars, the ease of taking a portrayal may allure them to share in health interventions (10). This type of facial recognition software has been used for colorful reasons including by the Department of Defense, and for felonious examinations, protection, and emotional recognition (11,12). still, increases and diminishments in weight in a single party can make it delicate for facial recognition technology to directly identify an existent (13). Recent work has examined ways to address changes in weight to ameliorate the delicacy of facial recognition software. former approaches have worked to examine changes in facial features due to weight change (13).

Research has shown that facial obesity demonstrated in photos of party faces has been appreciatively associated with their BMI (13), but there has been limited exploration on using this system to estimate an existent's BMI. The current study will be an extension of testing for the system developed by Guo and associates in 2013, which uses a computational approach to determine an existent's BMI from their facial features (14). As this has been the only study to develop this approach, further, streamlined disquisition of this system is demanded, aimed at perfecting the ease of dispersion of intervention programs that aim to capture health-grounded data. Guo teal's former approach used over 14,500 facial images of people of different age, race, and gender to formulate BMI prognostications (14). We propose now to use this system with a new cohort of individualities who have enrolled in a life intervention study and to prognosticate their BMI from their facial prints. The ideal of the current study was to test the effectiveness and community of a facial image algorithm for detecting the BMI of actors enrolled in a health intervention, and to compare the prognosticated fBMI to their physically collected BMI dimension.

II. METHODOLOGY

As part of a larger study, Get Freed, three cohorts of actors acceded as actors in this study and were enrolled and assessed (15). The cohorts included (1) upperclassmen council scholars (18 times or aged), who were mates in the development of the Get Freed peer-led social marketing crusade to increase healthier life among their incoming peers, (2) incoming newcomers at each university (four interventions and two control), and (3) a subproject of individualities enrolled in an 8-week salutary intervention aimed at adding fruit and vegetable consumption. All individualities were physically assessed at birth (August 2015) to capture anthropometrics of height, weight, and a facial picture by a trained experimenter. Weight was measured with minimum apparel on via a Tanita TBF-310GS Total Body Composition Analyzer (Garmin, Tanita Corporation of America, Arlington Heights, IL, USA). All measures were performed doubly and equaled for trust ability and delicacy. As eligibility criteria needed actors to be 18 times or aged, adult BMI measures were used (16).

BMI was calculated by dividing measured weight in kilograms by height in measures squared. groups of BMIS included <18.5 BMI (light), 18.5 –24.9(normal weight), 25.0 –29.9(fat), and ≥ 30 (fat). Facial images were contemporaneously taken along with birth assessments. prints were taken with digital cameras at each assessment point with actors standing against a neutral background with a neutral face, all eyewear removed, and hair removed from in front of the face. Actors held a white paper with their party ID in their print and prints were saved by ID number to insure obscurity of all enrolled.

To test the algorithm developed by Wen and Guo, facial images were anatomized by a facial corner sensor to identify a number of facial fiducial points, which were also used to cipher seven facial features. The seven facial features reckoned were automatically estimated and include impertinence to jaw range (CJWR), range to upper facial height rate (WHR), border to area rate (PAR), eye size (ES), lower face to face height rate (FW/ FH), and mean of eyebrow height (MEH). point normalization was executed and a retrogression function arrived at to represent the relation between facial measures and BMI values. This function was used to cipher the BMI for each test face image. reckoned facial BMIs(fBMI) were compared to physically measured BMIs(mBMI) through correlation analysis, matched brace comparisons, and conforming the perceptivity of the algorithm to detecting the trust ability of fBMI to mBMI. styles of assaying prints are explained in a former handwriting, but are generally described in Figure 1

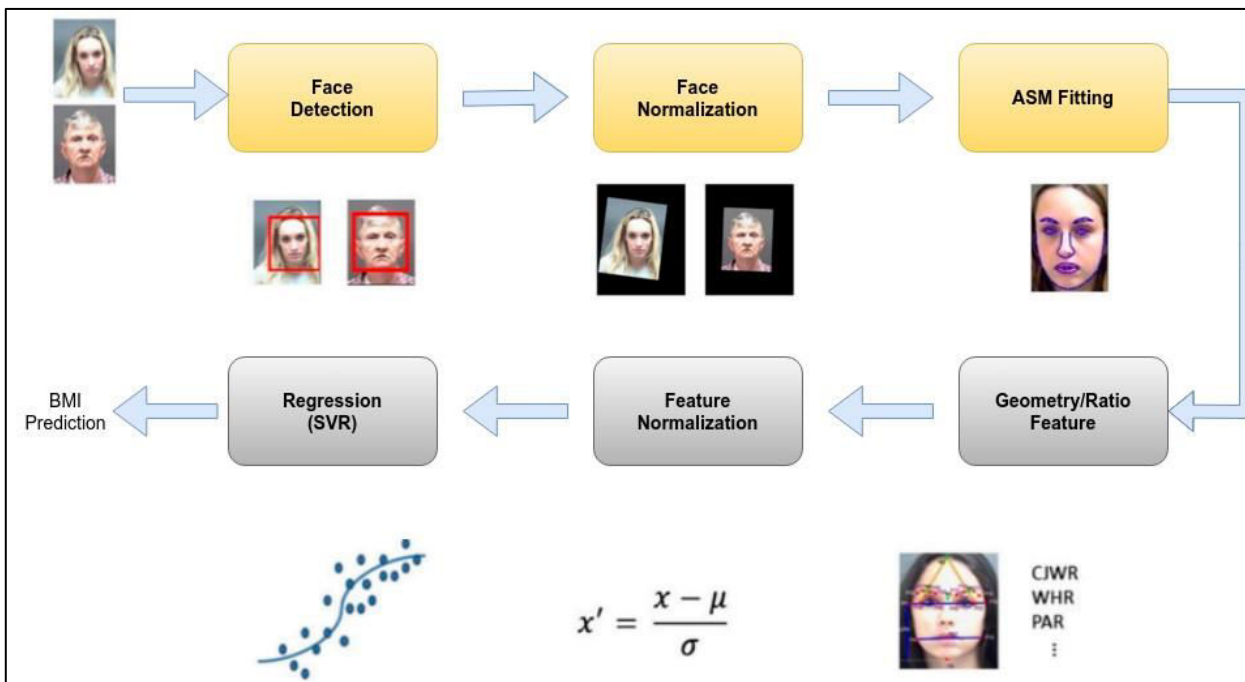


Figure 1. Proposed frame to prognosticate body- mass indicator (BMI) from facial image. Approach used by Wen and Guo (2013).

III. RESULTS

A sample of 1412 youthful grown-ups were assessed as part of a larger study. Sample size computation from this population size at 95 confidence position is 292 actors. Completed facial algorithm data were available on 1210 actors of the larger cohort. Actors were predominately Caucasian (62.5) and womanish (69.6), and were average of 19 times of age. Actors were predominately in the normal weight range order, with an mBMI of 18.5 –24.9 kg/ m²(60.2) (Table 1). Likewise, with fBMI actors were primarily detected to be in the normal weight order of BMI (81.9).

Pairwise correlation of mBMI and detected fBMI was significant ($r = 0.3070$; $p < 0.0001$). A retrogression model to prognosticate fBMI from mBMI also set up a significant relationship ($F = (11,208)125.7$; $p < 0.0001$). Table 2 shows the count data of actors in each mBMI order and their placement using fBMI. Data indicate that actors in the normal weight order were likely to be placed into the correct order by fBMI. still, the delicacy of fBMI fell for extreme orders of light and fat, and actors were inaptly placed. Contingency table analyses indicate that all 109 actors falling in the fat order of mBMI were placed into a lower order by fBMI (Table 2)

In comparing party placement using mBMI and fBMI, we set up that 60 of actors were placed in the correct order using fBMI. Table 2. Contingency table of measured body- mass indicator(mBMI) order placement and facial body- mass indicator(fBMI) order placement. mBMI groups of BMIS included <18.5 BMI (light), 18.5 –24.9(normal weight), 25.0 –29.9 fat), and ≥ 30 (fat). Total range 14.73 –49.74 kg/ m² for mBMI and 16.29 –28.85 kg/ m² for fBMI. Average fBMI was 23.7 ± 1.5 kg/ m² and average mBMI was 24.1 ± 4.5 kg/ m² Difference in average BMI was 0.4 ± 3.0 kg/ m² Matched brace comparison indicated that fBMI detected party BMI as kg/ m² lower than mBMI ($t(1209) = -3.39$, $p < 0.0007$). A matched brace plot shows analysis in Figure 2. When examining the mean absolute error (MAE) between mBMI and detected fBMI, we set up the MAE between the two results to be 3.2 ± 2.9 kg/ m² matched brace data plot shown as difference between algorithm- prognosticated facial BMI (fBMI) and objectively measured BMI (mBMI).

As gender is an important factor in BMI, Figure 3 graph shows difference between gender normal of algorithm prognosticated facial BMI (fBMI) and its relationship with objectively measured BMI (mBMI). Both circles following an analogous pattern analysis of MAE of mBMI and fBMI set up no significant differences between genders ($p = 0.1120$).

IV. DISCUSSION

Determining weight status through BMI is a generally employed parameter in health-related exploration studies (1). When applying exploration outside the vicinity of one's home university or exploration center, still, it may be grueling to gain anthropometric data similar as BMI. Our end in this study was to use facial photos and a preliminarily developed algorithm to estimate BMI (14). We also compared the estimated facial BMI to our objective BMI calculated from measured party anthropometrics to find bib rightly linked BMI in 58.4 of cases. fBMI was more accurate in normal weight and fat orders than in light and fat orders. As elevation is not included in the dimension for fBMI, it's possible that individualities who were considered fat by objective dimension were of short elevation, although their fBMI detected their facial features only as appearing fat. likewise, as our population was predominately in the 'normal' weight order, the algorithm had better odds at accurately detecting this order. Although the facial algorithm used in this study was nearly 60 accurate, trust ability in exploration is vital for accurate results and drawing conclusions. Kocbey et al. (17) examined social media profile filmland using both examined computer technology and factual mortal analyses of weight status to find that the computer and mortal judges detected analogous results for BMI from the prints, with a bitsy difference in results of lower than 2.

This demonstration that the algorithm used was veritably analogous to mortal visual judgment. An analogous study by Ancheta et al. (18) used single-shot facial images of predominately notorious individualities to determine BMI, as compared to the current system used by Wen and Guo. Ancheta et al. set up a lower range of error (MAE) in their BMI predications compared to Wen and Guo. Comparing the delicacy of the Wen and Guo system, we find a MAE value slightly advanced than Ancheta et al. (2.30.6), and at the high end of the range set up by Wen and Guo in their former work (2.65 –4.29) (14,18). Our findings show that when extending the operation of this algorithm to cooperative exploration sweats without the use of controlled prints, the error rate is within the range detected in former studies. A system analogous to Wen and Guo's was used by Wolffhechel and associates testing top factors performing from face shape and color features to find the stylish BMI predictor model using 2D star factors of both shape and color (20). still, the study had a small sample size ($n = 30$) and actors were needed to travel to the experimenters to be scrutinized by the 3D technology (20). This burden to the party isn't doable for dispersion of life interventions and this system doesn't farther the use of simple photos for detecting BMI, which remains the ultimate thing for perfecting the current system. When looking into the dispersion and perpetration of wisdom and the capability to take current interventions out of the laboratory for use with the public, exercising BMI as a simple measure can be vital to landing data on actors. There are several styles used for measuring BMI which have been explained then tone-reported measures, an intervention facilitator physically measuring actors, or the proposed facial image vaticination (14). The application of a simple 'selfie' from actors around the world sharing in the dispersion of interventions may bridge the gap between scientists collecting data and community use of systems. still, along with farther testing and perfecting of the fBMI algorithm, comparing the trust ability of tone-reported BMI to facial recognition BMI could be of interest in unborn exploration. tone-reported height and weight as well as BMI should be included in checks and questionnaires and correlations between mBMI, fBMI, and tone-reported BMI should be anatomized. Understanding the delicacy of both fBMI and BMI measures and perfecting the fBMI algorithm can enhance the dispersion and perpetration of exploration.

Our current study isn't without limitations. As with retrospective analyses and data mining post intervention, bias can be set up with significant results. still, the plan for this subproject was in place at the launch of the overarching design. We understand the bias of BMI, but as a gold standard for snappily measuring weight status, this was used to test for unborn intervention dispersion. We had a wide spread of individualities enrolled in this design; still, they were at four separate spots and dealt with different experimenters. Some prints were rendered unreadable by the algorithm and unfit to be used for analysis. still, to address implicit poor quality of the prints and trust ability of data capturing, experimenters at all spots were trained forester-rater trust ability. When addressing this issue moving forward, especially in dispersion exploration, stressing the significance of quality prints with a clear face will be imperative. We also set up considerable error of fBMI compared to mBMI. still, to our knowledge this was the first study using community experimenters to capture and test their own party photos for use with the algorithm. This system needs farther testing before it can be legitimately used by other experimenters and the public outside of pure exploration.

V. CONCLUSIONS

This current study aimed to use an algorithm to descry BMI from facial images of youthful grown-ups to ameliorate ease of data collection in dispersion exploration. Using party prints and performing a facial discovery algorithm to prognosticate BMI was effective for actors in the normal and fat orders of BMI. still for individualities falling in the

'extreme' orders of light and fat BMI, the algorithm was less effective. Further testing of this algorithm needs to be completed with fresh photos from community interventions.

REFERENCES

1. Yaemsiri, S.; Slining, M.M.; Agarwal, S.K. Perceived weight status, overweight diagnosis, and weight control among US adults: The NHANES 2003–2008 Study. *Int. J. Obes.* 2010, 35, 1063–1070. [CrossRef] [PubMed]
2. Centers for Disease Control and Prevention (CDC). Defining Adult Overweight and Obesity; Overweight & Obesity. Available online: <https://www.cdc.gov/obesity/adult/defining.html> (accessed on 28 August 2018).
3. Singh, A.S.; Chinapaw, M.J.M.; Brug, J.; van Mechelen, W. Process evaluation of a school-based weight gain prevention program: The Dutch Obesity Intervention in Teenagers (DOiT). *Health Educ. Res.* 2009, 24, 772–777. [CrossRef] [PubMed]
4. Pérez, A.; Gabriel, K.P.; Nehme, E.K.; Mandell, D.J.; Hoelscher, D.M. Measuring the bias, precision, accuracy, and validity of self-reported height and weight in assessing overweight and obesity status among adolescents using a surveillance system. *Int. J. Behav. Nutr. Phys. Act.* 2015, 12, S2. [CrossRef] [PubMed]
5. Mozumdar, A.; Liguori, G. Corrective Equations to Self-Reported Height and Weight for Obesity Estimates among U.S. Adults: NHANES 1999–2008. *Res. Q. Exerc. Sport* 2016, 87, 47–58. [CrossRef] [PubMed]
6. Pursey, K.; Burrows, T.L.; Stanwell, P.; Collins, C.E. How Accurate is Web-Based Self-Reported Height, Weight, and Body Mass Index in Young Adults? *J. Med. Internet Res.* 2014, 16, e4. [CrossRef] [PubMed]
7. Famodu, O.A.; Charlier, C.M.; Barr, M.L.; Colby, S.E.; Zhou, W.; Mathews, A.E.; Olfert, M.D. Self-reported vs. Measured Height and Weight in Young Adults. *FASEB J.* 2017, 31, 970–975.
8. Stommel, M.; Schoenborn, C.A. Accuracy and usefulness of BMI measures based on self-reported weight and height: Findings from the NHANES & NHIS 2001–2006. *BMC Public Health* 2009, 9, 421.
9. General, L. Submit a Selfie, Get a Quote for Life Insurance. Available online: <https://term.lgamerica.com/selfie-quote> (accessed on 28 August 2018).
10. Coyne, S.M.; Padilla-Walker, L.M.; Howard, E. Emerging in a Digital World: A Decade Review of Media Use, Effects, and Gratifications in Emerging Adulthood. *Emerg. Adulthood* 2013, 1, 125–137. [CrossRef]
11. Military. US military deploys facial recognition technology in Bin Laden operation. *Biom. Technol. Today* 2011, 2011, 1. [CrossRef]
12. Zebrowitz, L.A. Finally, Faces Find Favor. *Soc. Cognit.* 2006, 24, 657–701. [CrossRef]
13. Wen, L.; Guo, G.; Li, X. A study on the influence of body weight changes on face recognition. In Proceedings of the 2014 IEEE International Joint Conference on Biometrics (IJCB), Clearwater, FL, USA, 29 September–2 October 2014; pp. 1–6.
14. Wen, L.; Guo, G. A computational approach to body mass index prediction from face images. *Image Vis. Comput.* 2013, 31, 392–400. [CrossRef]
15. Colby, S.; Kattelman, K.; Olfert, M.; Mathews, A.; Kidd, T.; Brown, O.; Horacek, T.; White, A. "Get Fruved": A Peer-Led, Trained-the-Trainer Social Marketing Intervention to Increase Fruit and Vegetable Intake and Prevent Childhood Obesity. *J. Nutr. Educ. Behav.* 2015, 47, S109. [CrossRef]
16. Nissinen, K.; Mikkilä, V.; Männistö, S.; Lahti-Koski, M.; Räsänen, L.; Viikari, J.; Raitakari, O.T. Sweets and sugar-sweetened soft drink intake in childhood in relation to adult BMI and overweight. The Cardiovascular Risk in Young Finns Study. *Public Health Nutr.* 2009, 12, 2018–2026. [CrossRef] [PubMed]
17. Kocabey, E.; Camurcu, M.; Ofli, F.; Aytar, Y.; Marin, J.; Torralba, A.; Weber, I. Face-to-BMI: Using computer vision to infer body mass index on social media. *arXiv* 2017, arXiv:170303156.
18. Dantcheva, A.; Bremond, F.; Bilinski, P. Show me your face and I will tell you your height, weight and body mass index. In Proceedings of the International Conference on Pattern Recognition (ICPR), Beijing, China, 20–24 August 2018.
19. Wolffhechel, K.; Hahn, A.C.; Jarmer, H.; Fisher, C.I.; Jones, B.C.; DeBruine, L.M. Testing the utility of a data-driven approach for assessing BMI from face images. *PLoS ONE* 2015, 10, e0140347. [CrossRef] [PubMed]
20. Pascali, M.A.; Giorgi, D.; Bastiani, L.; Buzzigoli, E.; Henríquez, P.; Matuszewski, B.J.; Morales, M.-A.; Colantonio, S. Face morphology: Can it tell us something about body weight and fat? *Comput. Biol. Med.* 2016, 76, 238–249. [CrossRef] [PubMed]
21. Makenzie L. Barr, Guodong Guo, Sarah E. Colby, Melissa D. Olfert: Detecting Body Mass Index from a Facial Photograph in Lifestyle Intervention: *Technologies* 2018, 6, 83; doi:10.3390/technologies6030083.



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