ISSN: 2366-1313

ESTIMATE HEIGHT WEIGHT AND BMI FROM FACE USING DEEP LEARNING

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ABSTRACT:

Body height, weight, as well as the associated and composite body mass index (BMI) is human attributes of pertinence due to their use in a number of applications including surveillance, re-identification, image retrieval systems, as well as healthcare. Previous work on automated estimation of height, weight and BMI has predominantly focused on 2D and 3D full body images and videos. Little attention has been given to the use of face for estimating such traits. Motivated by the above, we here explore the possibility of estimating height, weight and BMI from single-shot facial images by proposing a regression method based on the 50-layers ResNet-architecture. In addition, we present a novel dataset consisting of 1026 subjects and show results, which suggest that facial images contain discriminatory information pertaining to height, weight and BMI, comparable to that of body-images and videos. Finally, we perform a gender based analysis of the prediction of height, weight and BMI.

Keywords*:*Deep Learning,BMI.

ISSN: 2366-1313

I INTRODUCTION

The body mass index or BMI processes the ratio between height and weight. The body mass index is the most basic tool which we use to define overweight and obesity. BMI is commonly regarded as a vital indicator of health. A normal BMI is between 18 and 25 and obesity starts at 30. With the gradual increase of body mass index, we notice a higher probability of cardiovascular diseases such as high blood pressure, diabetes, etc. A number in higher ranges leaves an individual at an exponential risk in health that the person has in addition to their BMI being raised, a waist circumference more than 40 inches. Therefore, classifies them into a greater risk category, so imperatively puts them up a risk category. Weight issues are directly linked to all chronic diseases. If things proceed the way they are now, it is believed that the next generation may not live as long this current generation.

The diet of an average overweight individual is one of the causes of this situation which contains various high-calorie fast food items. Even though after an individual eats these meals and gains energy, the energy lasts a very short period of time and causes hunger much sooner. The second reason is physical inactivity. The increased usage of the latest technology such as television, mobile phones, video games, etc has significantly reduced the physical activity of the average person. The third reason is stress. We are much less likely to exercise with the high amounts of stress and low sleep levels in our busy lives. Additionally, weight gain can be promoted, possibly due to hormonal and metabolic changes.

One more reason may be due to the environment we live in and our transportation system, which is overly dependent on cars. In many regions, there is an insufficiency of any form of public transportation systems, sidewalks, community parks, playgrounds and bike paths for recreational activities. On the other end of the spectrum, Adult malnutrition is more common and widespread than we are conscious of these days. Individuals obtaining a BMI value below 18 are considered underweight.

An issue in absorbing nutrients from food or consuming an inadequate diet is the root cause of malnutrition. The reasons for this can be many, consisting of having a low income, a long-term health condition or reduced mobility, etc. This result in a low mood, feeling tired all the time, weak muscles, slow or impaired growth, etc. Another major concern is that people that are overweight can be undernourished if they consume a high-calorie diet but are low in other essential nutrients.

It becomes really difficult for a common individual to measure their BMI values given that people have less time in their busy life and most people do not own a weighing machine and/or a measuring tape. In order to involve more people to measure their BMI, we propose an exciting measuring process and therein spread more awareness. In this paper, we propose a novel method to calculate the BMI of an individual from their face by the use of Deep Learning models.

The prediction of deep learning model is largely considered as a black box process. Some reasons to explain the results can be due to the changing of facial features at varied weight ranges. Overweight individuals have widened mid and lower faces, widened nose and a reduced eye height relatively to underweight individuals, who have an angular face with a pointed chin and relatively narrower cheeks. In addition to calculating the BMI, the height and weight of an individual is also calculated in this paper. This can be helpful for gaining knowledge of the physical appearance of a person, which otherwise may not be possible.

II. LITERATURE SURVEY

1.BMI and WHR Are Reflected in Female Facial Shape and Texture: A Geometric Morphometric Image Analysis, Christine Mayer, Sonja Windhager, Katrina Schaefer, Philipp Mitteroecker(2022).

Facial markers of body composition are frequently studied in evolutionary psychology and are important in computational and forensic face recognition. We assessed the association of body mass index (BMI) and waist-to-hip ratio (WHR) with facial shape and texture (color pattern) in a sample of young Middle European women by a combination of geometric morphometric and image analysis. Faces of women with high BMI had a wider and rounder facial outline relative to the size of the eyes and lips, and relatively lower eyebrows. Furthermore, women with high BMI had a brighter and more reddish skin color than women with lower BMI. The same facial features were associated with WHR, even though BMI and WHR were only moderately correlated. Yet BMI was better predictable than WHR from facial attributes. After leave-one-out crossvalidation, we were able to predict 25% of variation in BMI and 10% of variation in WHR by facial shape. Facial texture predicted only about 3–10% of variation in BMI and WHR. This indicates that facial shape primarily reflects total fat proportion, rather than the distribution of fat within the body. The association of reddish facial texture in high-BMI women may be mediated by increased blood pressure and superficial blood flow as well as diet. Our study elucidates how geometric morphometric image analysis serves to quantify the effect of biological factors such as BMI and WHR to facial shape and color, which in turn contributes to social perception.

2. "Al - based BMI Inference from Facial Images: An Application to Weight Monitoring" by Hera Siddiqui et al. (2020).

In order to estimate BMI, this study suggested a unique end-to-end CNN network. With the use of pertained CNN models including VGG-19, ResNet, Dense Net, MobileNet, and LightCNN, the authors additionally retrieved characteristics from the facial photos and then uploaded them to SVR and RR for final predictions. With the support of the VisualBmi, VIP attribute, and Bollywood Datasets, they were able to attain Mean Absolute Error (MAE) values between [1.04] and [6.48]. Ridge Regression improved the performance of DenseNet and ResNet models. Ridge Regression improved performance when pertained models were employed. Pertained models outperformed the end-to-end CNN model to some extent.

3. "On Visual BMI Analysis from Facial Images. Image and Vision Computing "by Jiang et al. (2019).

The authors of this study examined the accuracy of predictions using geometry-based and deep learning-based methods for calculating visual BMI. They also evaluated the impact of various variables like gender, ethnicity, and head attitude. Deep learning-based approaches produced superior outcomes than geometry-based, but because training data is extremely scarce, the large dimensionality of features has a detrimental effect. Large head posture changes also have a negative impact on performance. The authors' FIW-BMI dataset and the Morph II dataset are both derived from social media platforms.

III SYSTEM ANALYSIS

EXISTING SYSTEM

Estimating body height, weight and the associated BMI is warranted for several reasons. Firstly height and weight are attributes frequently used in surveillance, forensics, as well as re-identification applications and image retrieval systems Secondly, height and weight are primary and obvious attributes used by humans to verbally describe a person often used in police reports, unlike traditional biometrics which may be insufficient, as this was argued, for example, by Klontz and Jain in the case of the 2013 Boston bombings. Thirdly, body weight and height have been proposed as soft biometric traits in automated biometric systems. Fourthly, weight is a pertinent indicator for health and excessive weight has been associated to obesity, diabetes, and cardiovascular diseases. In this context, the presented method contributes to the current trend of image-based automated self-diagnostic. Finally, this work can promote research conducted in psychology related to human metrology.

Limitations of Existing System

- Computational power (Depends on network architecture and data size) Complex architecture(Not every time

PROPOSED SYSTEM

Motivated by the above, we propose here a method for face-based estimation of height, weight and BMI based on the ResNet-50 architecture. We pose the problems of height, weight and BMI estimation as 3 separate regression pattern classification problems. We employ face detection prior to the ResNet as an attention mechanism. While deep neural networks (DNNs) tackle challenging settings of attributes in the wild that encompass complex face variations such as poses, lightings, and occlusions reasonably well and generally no face detection is required, we ensure by detecting the face, that nobody information is considered in our study and hence we analyze the face-based height, weight and BMI estimation. In what follows, we proceed to describe briefly the preprocessing step of face detection and the employed ResNet architecture.

Proposed system Advantages:

- Learning of accurate pattern and insights from the provided data.(Depends on how well structured, clean or feature engineered the data is)
- One can tune the network to achieve better and accurate results.
- Can provide better outcomes than other machine learning algorithms if tuned better and feuded a good amount of data.

ISSN: 2366-1313

IV IMPLEMENTATION

Architecture:

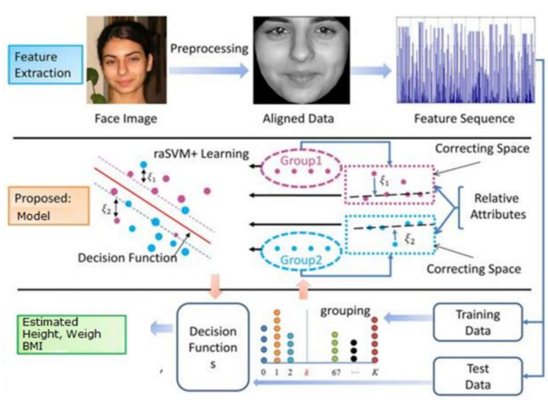


Fig-1. Architectures of the system model

MODULES:

1. Face Detection: In the Face-to-BMI and Reedit-HWBMI datasets, both contain images with close-up shots of individuals. But to make sure our model only considers the facial features of an individual, we apply facial detection beforehand. For this purpose, we use the commonly used Voila-Jones Face Detection algorithm using OpenCV

2. Data Preprocessing: The detected faces are cropped and saved to be images of size 256X256. Additionally, the per-pixel mean has been subtracted for each of the two datasets. Then, a 224X224 crop is randomly sampled from each image or it's horizontal.

3. Feature Extractor:

Xception Net (best for BMI and weight) - pre-trained on Image Net dataset.

VGG-Face (Resnet-50) (best for height) - pre-trained on VGG-Face dataset.

4. Artificial Neural Network:

The features extracted from the feature extraction model are fed into an Artificial Neural Network model consisting of 3 layers. The three layers are 256-d fc, 64-d fc and 1-d fc layer respectively. The output is a 1 dimensional floating point value. The loss function used is smooth L1 Loss for this regression problem. Afterward, we fine-tune the finer strides of our model using the Face-to-BMI dataset and Reedit-HWBMI dataset separately.

Testing

In this phase the system is tested. Normally programs are written as a series of

ISSN: 2366-1313

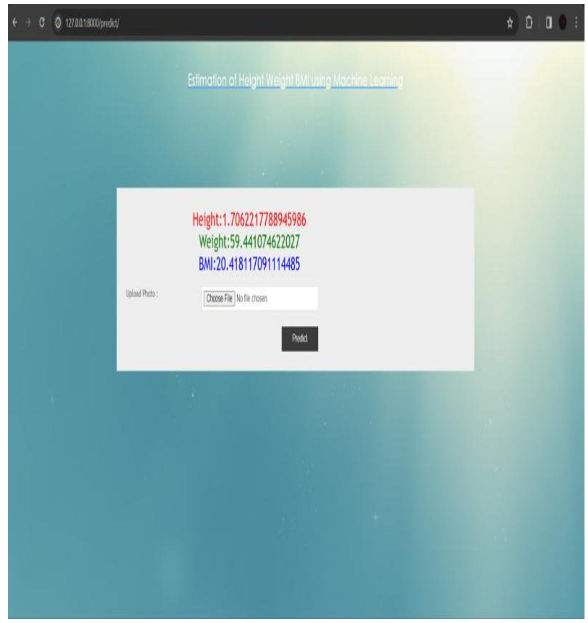
individual modules, this subject to separate and detailed test. The system is then tested as a whole. The separate modules are brought together and tested as a complete system. The system is tested to ensure that interfaces between modules work (integration testing), the system works on the intended platform and with the expected volume of data (volume testing) and that the system does what the user requires (acceptance/beta testing).

Maintenance

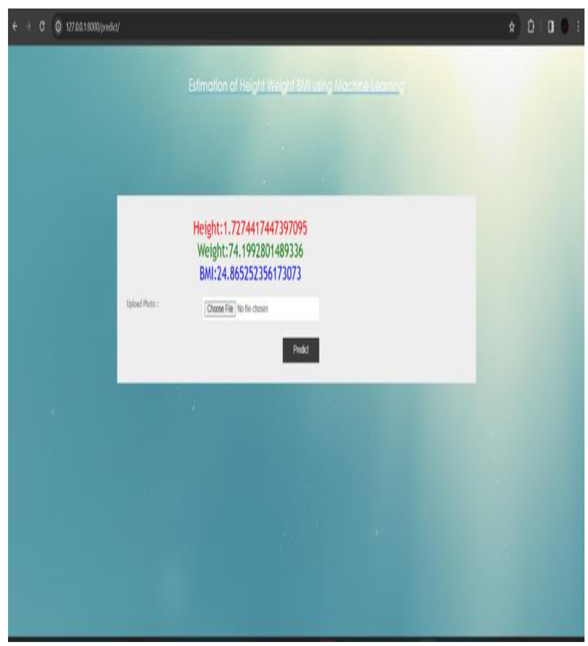
Inevitably the system will need maintenance. Software will definitely undergo change once it is delivered to the customer. There are many reasons for the change. Change could happen because of some unexpected input values into the system. In addition, the changes in the system could directly affect the software operations. The software should be developed to accommodate changes that could happen during the post implementation period.

V RESULT AND DISCUSSION

Home page:



Output 1:



Output2:

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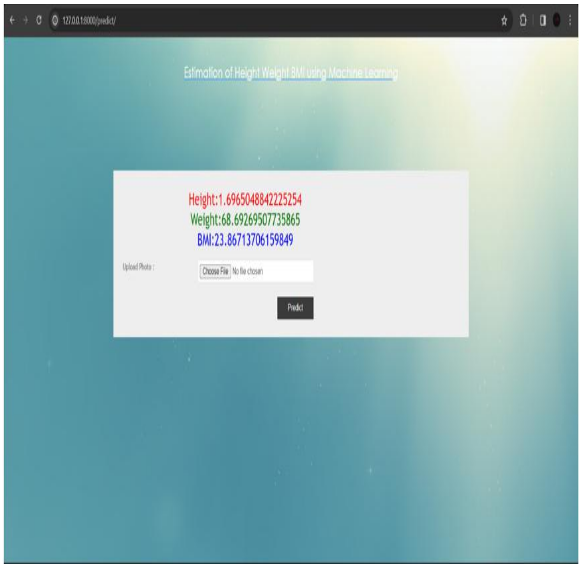

VI CONCLUSION

We have presented a novel method to compute the Height, Weight and Body Mass Index of an individual. We have created our own dataset consisting of face images 982 individuals along with their height, weight and BMI. Additionally, we have also evaluated our model on the Face-to-BMI dataset which contains face images of 3368 individuals along with their BMI values. The model process starts with face detection on the preprocessed data using Voila-Jones algorithm. The images are fed to a feature extractor model. The extracted features are put into a custom Artificial Neural Network (ANN) which produces the predicted outputs for our regression problem. The best performance for BMI was given by the XceptionNet model when used as a Feature Extractor with Mean Absolute Error (MAE) value of 4.1 and 3.8 for Reddit-HWBMI dataset and Face-to-BMI dataset respectively. The XceptionNet also performed best for weight having MAE(in kg) value of 13.29, whereas VGG-Face (Resnet model) performed slightly better than XceptionNet for height having MAE(in m) value of 0.073 on the Reddit-HWBMI dataset.

FUTURE ENHANCEMENT

In our future work, we would work on implementing new ideas to improve our models performance. This paper was motivated by the need to create awareness for health amongst our society, which usually gets neglected in our busy lifestyle.

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ISSN: 2366-1313

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