Review on Image-based Body Mass Index Prediction Methods

Sruthy R[1]

[1]Guest. Lecturer, Dept. of Electronics and Communication Engineering, NSS Polytechnic College, Kerala, India

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Abstract –*An individual's body mass index (BMI), is a measure based on height and weight, that assesses a person's level of body fat. It is a tool to identify whether an individual is underweight, overweight, or healthy. Health risks may increase if a person's BMI is not within the healthy range. Traditional BMI assessment is prone to accuracy issues. This has a negative impact on determining a person's fitness. With the emergence of technologies, several image processing techniques have been developed to estimate body mass index from human body images. This paper is a review of different image-based BMI prediction methods.*

Key Words: ***Body Mass Index (BMI), Anthropometric features, Conditional Random Field Recurrent Neural Network (CRF-RNN), Support Vector Machine (SVM), Support Vector Regression (SVR), Region aware Global Average Pooling method (Re-GAP) Magnetic Resonance Image (MRI), Gradient-Weighted Class Activation Mapping (Grad-CAM), Rectified Linear Unit (ReLu), Residual Network(ResNet)***

1. INTRODUCTION

The ratio between the weight and height of a person can be expressed as a number called body mass index (BMI). It could provide a fundamental understanding of someone's weight status [1]. It is measured commonly using a device called scale or balance. Several use cases require an assessment of body weight without the direct presence of the person. With the advancement of image processing methods, it is now possible to predict BMI from body images without knowing a person's height or weight.

A person's weight can be difficult to measure using a weighing machine when they are in medical emergencies because they can't be moved. A weight estimation could have a great deal of value in forensic science as well. An automatic search through video surveillance records could utilize weight along with other physical traits to describe the fugitive [2]. This article discusses various image processing methods that can be used as an alternative approach to accurately calculate a person's body mass index. In Chapter 3, the different BMI estimation methods are discussed. The comparison of these approaches is presented in Chapter 4. The conclusion of the work is given in Chapter 5.

2. LITERATURE REVIEW

A computational model for BMI estimation using two-dimensional human body images has been proposed in [3]. In this type of model, an estimation of BMI is based on a single or pair of two-dimensional body images. This model maps weight/BMI values based on five anthropometric features taken from body images. The method can categorize the weight variance from pairs of photos. The classification task is done by Multi Support Vector Machine (SVM) and BMI prediction is done by Support Vector Regression (SVR).

A facial image-based BMI prediction system has been implemented in [4]. Face Net and VGG face and Region aware Global Average Pooling method are used to extract the facial features from the images. Then the feature vectors obtained are fed to the regression module to predict the body mass index.

In [5], a deep learning-based approach has been employed to estimate body mass index from structural Magnetic Resonance images (MRI). The CNN localization maps revealed the caudate nucleus and the amygdala as brain regions that contributed strongly to BMI prediction. Gradient information from the final layer of the CNN is used in a method known as gradient-weighted class activation mapping (Grad-CAM)[6] to identify brain areas that are significantly connected to BMI prediction.

In [7], BMI is assessed from silhouette images utilizing convolutional neural networks. Silhouettes represent objects, people, or scenes in one color, typically black, with edges corresponding to the contours of the subject [8]. For estimating BMI, six machine learning models and MiniVGGNet deep learning model are employed. When these 7 models' performance is compared, it is discovered that CNN outperforms the other 6 machine learning models. The 6 machine learning models are Gabor-RF (Random Forest), HOG (Histogram of Gradient)-RF, Gabor-XGB(XGBoost), HOG-XBG, Gabor-SVM (Support Vector Machine), and HOG-SVM.

A deep ResNet model for determining Body Mass Index has been given the depth image of the individual obtained from the Kinect Sensor in [9]. In order to train the deep neural network model to predict BMI scores, the suggested method generates a significant amount of synthetic depth pictures of virtual manikins. Making use of the MakeHuman software, 3D manikins are developed.

Body mass index has been determined from facial image features using the logistic regression model in [10]. The method makes use of two distinct datasets that are composed of different kinds of face image data. Seven essential geometrical indications are calculated based on face reference points. The performance of the suggested strategy was validated and verified using Mean Absolute Error (MAE). The Autocorrelation Coefficient is used in this study to describe the texture characteristics of the facial skin.

3. METHODOLOGY

This study discusses the noninvasive methods of BMI estimation thereby eliminating the necessity to weigh people. Image-based BMI estimation methods are presented in this section. This includes body mass index prediction from Body images, MRI images, face images, etc.

3.1 BMI from 2D body images

A non-invasive BMI estimation approach has been proposed in [3]. The three-step body weight assessment in this method is as follows: identification of skeleton joints and body contours, computation of anthropometric features from the 2D body photographs, and utilization of statistical models to map these attributes to weight disparities or BMI readings. For feature extraction, body contours and skeletal joints (CSJs) are detected first using a Conditional Random Field Recurrent Neural Network (CRF-RNN)[11].

Anthropometric features are computed from the output of the detection. The five anthropometric features include waist width to thigh width ratio (W T R), waist width to hip-width ratio (WHpR), waist width to head width ratio (WHdR), hip-width to head width ratio (HpHdR), and body area between waist and hip (Area). Recognition of weight differences is a three-class categorization task. Weight variance can be categorized using the method from pairwise pictures. There are three output values, 0 as an indicator for no weight changes, 1, as an indicator for increased weight, and -1 as an indication of decreased weight. Two distinct regression models are used to predict both the BMI values and the BMI discrepancies.

3.2 Facial image-based BMI prediction system

Deep features taken from various face regions of face images are utilized in this method [4]. At first, the face detection method is used to crop the face region. A face region mask is generated by segmenting a face semantically. High weight is then given to different face regions by multiplying elementwise the masks with the convolution feature maps. After that, each masked convolution map is pooled separately based on the global average pooling. To obtain BMI predictions, the regression module is used.

3.3 MRI-based BMI assessment system

The DL technique has been successfully applied to estimate an individual's BMI from an MRI scan, suggesting a correlation between cortical areas and body weight in [5]. The CNN employed in this system consists of repeated 3D spatially separable convolutional layers that are first normalized and then activated by rectified linear units (ReLUs). For BMI prediction, the feature maps from the last block are mapped to a vector using global average pooling. A modified version of the Grad-CAM was used to create localization maps for recognizing brain areas related to BMI prediction. It seeks to offer visual justifications for the choices taken by numerous CNNs.

3.4 CNN-based system using Silhouette images

Here, BMI is estimated from silhouette images generated from two-dimensional photographs [6]. This type of image decreases the data intricacy. Six machine learning models Gabor-RF, HOG-RF, Gabor-XGB, HOG-XBG, Gabor-SVM, HOG-SVM, and MIniVGGNet[12], a scaled-down version of VGGNet is used for the BMI prediction task. Gabor filter and HOG descriptor are used for feature extraction. CNN outperforms all other models and performs better on fit metrics like the Co-efficient of Determination, yields a smaller maximum error, and performs better by a factor of more than 2x on the Mean Squared Error . The initial input filters are followed by two CONV => RELU => BN => POOL layers in the MiniVGGNet design.

3.5 Skeleton-free Kinect Sensor-based System

The suggested approach is based on producing enormous quantities of synthetic depth images of virtual manikins using the ResNet model for estimating BMI scores [8]. The depth images are captured by Kinect Sensor [13]. MakeHuman software is primarily used to create 3D manikins and anthropometric measurements are taken from the manikins. Then the body surface area of the created manikin is also determined. To render depth pictures from the made 3D models, 'Blender' software is used. Deep ResNet is trained using the depth pictures encoded from the point cloud to produce a BMI value.

3.6 Facial Morphological Cues-based System

The system made use of the VIP Attribute dataset and MORPH-II dataset. Each dataset was split up into two collections of facial photographs, Set-1, and Set-2. The facial images for each category were randomly selected. Seven features—CWJWR(Cheekbone width to Jaw width ratio), CWUFHR(Cheekbone width to Upper Facial Height

No	Title	Techniques	Data
1	Body Weight Analysis from Human Body Images [3]	RF-CNN SVM SVR	2D human body images
2	Estimation of BMI from Facial Images using Semantic Segmentation based Region-Aware Pooling [4]	Face semantic segmentation, Region-Aware pooling Regression	Face image
3	Predicting body mass index from structural MRI brain images using a deep convolutional neural network [5]	Grad-CAM CNN	MRI brain image
4	Estimation of Body Mass Index from Photographs using Deep Convolutional Neural Networks [7]	MiniVGGNet	Silhouette Image generated from photographs
5	A skeleton-free kinect system for body mass index assessment using deep neural networks [9]	Kinect Sensor ResNet	Depth Image of body
6	Body Mass Index Prediction and Classification Based on Facial Morphological Cues Using Multinomial Logistic Regression [10]	Multinomial logistic regression	Facial Morphological Cues

Table 1: Comparison table

Ratio), PAR (Perimeter to Area of polygon), ASoE(Average Size of Eye), FHLFHR((Face Height to Lower Face Height Ratio), FWLFHR((Face width to Lower Face Height Ratio), MEH(Mean of Eyebrow Height), and texture feature—are retrieved and used in conjunction with the MLR model to forecast how the BMI and other factors are related to face cues. The pictures in Set-1 are used to determine the MLR model coefficients. The LASSO [14] technique is used to predict the model coefficients. Each face image in Set-2 is fitted with the MLR (Multinomial logistic regression model)[14] based on the calculated coefficients, and the BMI is estimated and categorized into one among the four BMI categories (Underweight, Normal Weight, Overweight, Obese).

4. COMPARISON

The comparison of various image-based BMI assessment techniques is shown in Table 1.

5. CONCLUSION

The body-mass index (BMI), which measures a person's mass in relation to their body size, is a crucial determinant of their weight status [16]. There are numerous uses for BMI data, ranging from the health sector to social networking apps. Various equipment is often used to assess BMI in person. The development of technology led to the development of several methods that estimate BMI without taking into account a person's height and weight. Through the extraction of features related to BMI from body images, face images, MRI images, etc., these systems assess BMI. This paper presented the various approaches for BMI assessment using these images. It is found that, when trained properly and equipped with the right personnel, image processing approaches can be used in place of traditional techniques for calculating BMI [17].

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