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USE OF DEEP LEARNING FOR BMI ESTIMATION FROM FACIAL IMAGE

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Abstract - A person's Body Mass Index, or BMI, is a crucial indicator of their health. It establishes if the individual is overweight, obese, underweight, or normal weight. It serves as a measure of an individual's health in connection to their body weight. In general, fat people tend to have broader faces in the center and lower regions. The person finds it difficult to determine their BMI without a scale and measuring tape. To create an approach that predicts BMI from human faces, this method correlates BMI with human faces using deep learning and transfer learning models such as VGG-Face, Inception-v3, VGG19, and Xception. Three publicly available datasets including images of both prisoners and non-offenders (Arrest Records Database, VIP-Attribute Dataset, and Illinois DOC dataset)

The front-facing pictures were made with superstars from Hollywood. The images could be shaky, crooked, or even feature captions. They are made to look alike using a method called StyleGan. After that, the face is vertically aligned using the DLIB 68 face landmark detection model, and the background is blurred to make the face stand out. The individual's BMI is obtained by adding the entire network of interconnected layers from the pre-trained model. Compared to the current system, the existing methodology is notably different since it utilizes pre-trained models such as Inception-v3, VGG-Face.

Key Words: Body Mass Index prediction, Face To BMI, Deep Learning, Facial Features, StyleGan, DLIB 68.

1. INTRODUCTION

The Body Mass Index (BMI) is a widely used metric that determines an individual's general weight condition by calculating the ratio of height to weight. A lot of factors have been connected to BMI, such as popularity, mental and physical well-being, and physical health. Precise weight and height measurements are often required for BMI estimates, requiring labor-intensive manual labor. The Body Mass Index (BMI) of each individual is a crucial indicator of their health. It is established if the individual is underweight, normal, overweight, or obese. One of the things that is still most ignored is health. Even highly advantageous technologies have drawbacks. People have become more lethargic as a result, which has reduced their level of physical activity, led to a sedentary lifestyle, and increased BMI pose a danger of chronic diseases and are detrimental to their health. The probability of obtaining

As BMI rises, the risk of cardiovascular and other dangerous diseases increases. However, some persons experience problems like as hunger and inadequacy. Based on BMI measurements, a person can be classified as underweight (BMI <18.5), normal (BMI ≤25), overweight (25<BMI <30), or obese (BMI <30). BMI can help an individual monitor their health.

A person's looks can reveal a lot about them. There is a strong correlation between a person's BMI and their facial features, according to recent studies. Individuals with slender faces are probably lower BMIs, and vice versa. Those that are obese usually have larger bottom and middle face features. It might be difficult to determine someone's BMI if they do not have a scale or measuring gadget. Recently, great progress has been achieved in deep learning, allowing models to extract meaningful information from photographs. By using these methods, we may infer the BMI from the faces of people. Consequently, in this study, we have proposed a method to estimate BMI from human faces.

2. OBJECTIVES

The following are the objectives of the suggested system:

- To enhance the quality of the photos by pre-processing the dataset's inconsistent images.
- To straighten the face in a skewed image.
- To use facial trait extraction from photos to predict BMI.
- To predict Body Mass Index from previously pre-processed facial pictures using deep learning.

3. LITERATURE SURVEY

i. Lingyun Wen and Guodong Guo's (2013) paper, "A computational approach to body mass index prediction from face images,"

The BMI in this study was computed. The scientists extracted seven facial features from face photos by using the Active Shape Model to extract facial landmarks. Among these seven qualities are CJWR, ES (Eye Size), The measurements of face proportions include FW/FH (Lower Face to Face Height Ratio), MEH (Mean Eyebrow height), WHR (Width to Upper face Height Ratio), PAR (Perimeter to Area Ratio), and CHJ (Cheek to Jaw Width Ratio). The Support Vector Regressor (SVR), Least Square Estimation, and Gaussian Process were then used to solve the regression problem. They used the Morph II dataset for evaluation and training. The results showed that SVR produced the best results for both sets of data. Using a similar technique, Barret al. presented the estimate of Facial BMI (fBMI) from facial measures. In terms of evaluation, the normal and overweight groups showed a stronger link between fBMI and BMI, whereas the underweight and obese groups showed a weaker correlation.

ii. E. Kocabey and colleagues' article "Face-to-BMI: Using Computer Vision to infer Body Mass Index on Social Media" (2015):

A computer vision algorithm was proposed by Kocabey et al. to predict an individual's BMI based on photos they shared on social media. The VisualBMI Project provided the images. In order to extract deep features from the 4206 face pictures, they used the VGG-Net and VGGFace models. They have used an epsilon-equipped support vector regression model in case of BMI decline. When compared to VGG-Net, VGG-Faces performed better. Pearson correlation coefficients of 0.71, 0.57, and 0.65 were obtained for the Male, Female, and Overall categories in the test set of the VGG-Face model. Furthermore, they displayed forecasts made by both robots and people.

iii. A new technique for estimating body mass index, weight, and height from face photos was developed by Ankur Haritosh and colleagues in 2019:

Using facial photos, this study suggested a whole new method for determining BMI, height, and weight. 4206 photos from the VisualBMI project and 982 photographs from the Reddit HWBMI dataset were used. The Voila Jones Face Detection method is applied, and the images are cropped to 256256. Once high-level features have been extracted from these photos by the feature extractor model, they are given to the 3-layered ANN model. The Reddit HWBMI dataset and the Face to BMI dataset showed that the MAE for BMI using XceptionNet was 4.1 and 3.8, respectively.

iv. Christine Mayer and colleagues (2017) conducted a geometric morphometric image analysis and found that "BMI and WHR Are Reflected in Female Facial Shape and Texture": This study used a statistical methodology to find the relationship between waist to hip ratio (WHR), body mass index (BMI), and facial form and texture. 119 anatomical landmarks and semi-landmarks were identified by the authors using the Windows application TPSDig. Using a sliding landmark technique, they were able to precisely estimate the locations of semi-landmarks. In their investigation, 49 standardized images of women with WHRs ranging from 0.66 to 0.82 and BMIs between 17.0 and 35.4 were included. Procrustes shape coordinates are used to depict the face's contour, while RGB values from standard pictures are used to represent its texture.

v. "Regarding Facial Image-Based Visual BMI Analysis. Jiang et al. (2019) published "Image and Vision Computing."

In order to determine visual BMI, the authors of this study looked at the prediction accuracy of two different approaches: deep learning and geometry-based. The effects of other variables, such as gender, ethnicity, and head attitude, were also assessed. The huge dimensionality of features has a negative impact since training data is extremely rare, although deep learning-based approaches outperformed geometry-based approaches in terms of output. Performance is also negatively impacted by large head position shifts. Both the Morph II dataset and the FIW-BMI dataset created by the authors are taken from social media sites.

vi. Hera Siddiqui et al.'s "Al-based BMI Inference from Facial Images: An Application to Weight Monitoring

This paper proposed a novel end-to-end CNN network to assess BMI. The authors also extracted features from the face pictures using pre-trained CNN models, such as VGG-19, ResNet, DenseNet, MobileNet, and LightCNN. They then uploaded the features to SVR and RR for final predictions. They were able to obtain Mean Absolute Error (MAE) values between [1.04] and [6.48] with the use of the VisualBmi, VIP attribute, and Bollywood Datasets. DenseNet and ResNet models performed better when using Ridge Regression. When pretrained models were used, performance was enhanced via Ridge Regression. To a certain extent, trained models performed better than the end-to-end CNN model.

4. METHODOLOGY

Convolutional Neural Networks (CNNs) in Python are used in the suggested system to calculate Body Mass Index (BMI) using facial image data. It uses a face image as input, preprocesses it (e.g., by downsizing and converting to grayscale), and then uses CNN to extract facial features. After that, a regression model is employed to map these features to a BMI number in order to estimate the person's BMI in the picture.

Utilizing a collection of face photos with known BMI values, the CNN is trained to learn how to correlate facial traits with BMI. The accuracy of the system is assessed on a different dataset following training. After being taught and assessed, the system can be used to calculate BMI from fresh face photos, providing a potentially useful medical tool.

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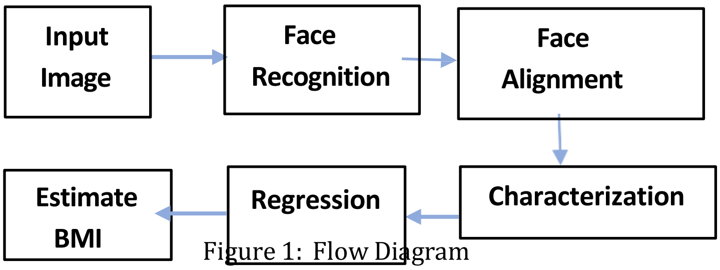

Figure 1: Flow Diagram

1. Enter the image

The dataset's front-facing image is uploaded to the application and utilized as the input.

2. Recognition of Faces

The face detection module loads the BMI detection CNN model and the facial detection CV2 library. In order to forecast BMI, facial features are included to the CNN model when a human face is spotted in an uploaded image.

3. Setting the Face in Alignment

This module's job is to analyze the features of the face. For example, if the input is skewed or fuzzy, the image is aligned and magnified for pre-processing, which is done with the DLIB 68 landmark model and the StyleGan approach.

4. In-Depth Characterization

This module explains how to feed input data to a pre-trained CNN and then retrieve the right activation values from the many pooling layers (present at different levels) or from the fully connected layer (usually at the network's end). Regression is used to streamline the output generated during the actual process of deep feature extraction.

Regression:

Regression analysis is a statistical technique mainly employed for outcome prediction, future event prediction, time series modeling, and causal relationship identification. Regression analysis entails drawing a graph between the variables that most closely matches the provided data points. This plot can then be used by the machine learning model to predict the data.

5. Estimating Body Mass Index

In this last module, the face is taken out of the given input image, and the features are examined as previously mentioned in the other modules in order to finally predict the BMI. If a person is overweight or underweight, it can be quickly ascertained using their predicted BMI.

5. ARCHITECTURE

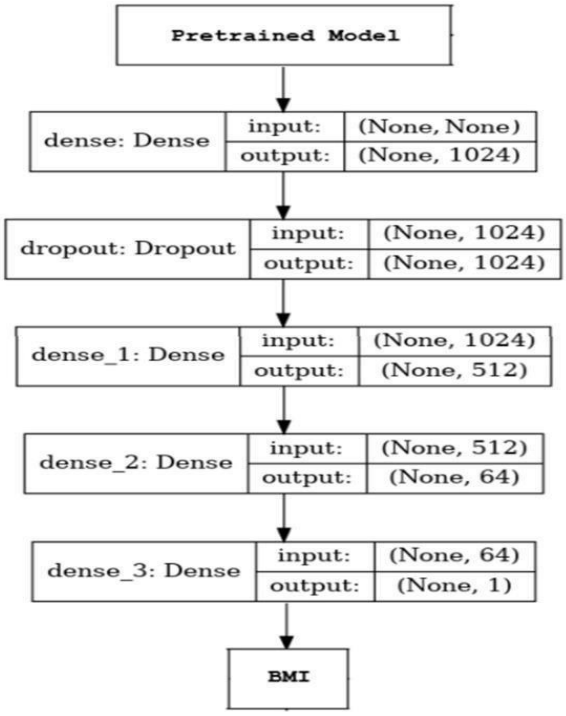

Figure 2: Model architecture for the project

- The completely linked layers at the end are used in all pre-trained models. The final layers that are applied are seen in Figure 2.
- Before feeding the output of the pre-trained model into the fully linked layers, we perform Global Average Pooling. To avoid overfitting, the model architecture shown in the above figure has one dropout layer with a 50% dropout.
- Furthermore, the features of the RELU activation function, Dropout, and Zoneout are combined in the Gaussian Error Linear Unit (Gelu) activation function, which is depicted in Figure 2 of the Model Architecture.
- Because it tends to generalize better when there is more noise in the data, it is used in the architectural model. If a substantially larger dataset is used, the prototype can be made better.
- Because deep convolutional networks' layers near the input acquire basic qualities like edges and corners, the layers usually acquire more sophisticated features as the design moves toward the output. The pre- trained model employs a reduced learning rate for some of the final layers and a greater learning rate for the new fully connected layers in order to extract more attributes from the photographs.from the photos, it uses a higher learning rate for the new fully connected layers and a significantly lower learning rate for some of the final layers.

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6. RESULTS

The design, model, and hence the difficulties of the current system are manifestly outweighed by the benefits of the suggested alternative. The suggested approach allows for the classification of any titled, blurry, distorted, or inconsistent images in addition to the previously used faces that are not aligned to the center, thus saving time and improving performance. The previous system made extensive use of the active shape model, but this has been eliminated by applying preprocessing techniques like StyleGAN, which makes inconsistent images similar. Next, the DLIB 68 Landmark model is applied, which aligns, zooms in, and blurs the background while focusing on the face.

Image	Gender	Predicted BMI	Actual BMI
A00147	Male	31.47	29
A00360	Male	27.67	24.7
A01072	Male	33.90	29
Shereen	Female	21.33	18.9
Shreya	Female	17.68	17.5
Yamini	Female	21.9	18.9
A00367	Male	47.86	33.2
A01148	Male	31.78	23.7

Figure 3: Comparison between Actual and Predicted BMI

Considering the relative difference between the actual BMI and the predicted BMI, the accuracy acquired is 80.5%.

7. CONCLUSIONS

It has been discovered that people who have higher BMIs are more susceptible to health issues. Researchers have found a strong relationship between a person's face and BMI. Consequently, a deep learning approach is proposed to estimate BMI using facial photo data. The BMI is calculated by analyzing the face features using Python's CNN (convolution neural networks) approach.

CNN uses an image as its input and extracts the face features from it before determining BMI based on those factors. The facial data is pre-processed and the faces are centered using the BMI detection algorithm. The method will be applied in future studies to replicate obesity rates at the population level with photos from social media accounts.

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