PREDICTION OF BMI FROM FACIAL IMAGE USING DEEP LEARNING

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Abstract - *Any person's BMI (Body Mass Index) is an important sign of their health. It determines whether the person is underweight, normal weight, overweight, or obese. It is a gauge of a person's health in relation to their body weight. Typically, the centre and lower parts of the face are wider on fat people. Without a measuring tape and a scale, it is challenging for the person to calculate their BMI. This method uses deep learning and transfer learning models like VGG-Face, Inception-v3, VGG19, and Xception to discover a correlation between BMI and human faces in order to develop a strategy that predicts BMI from human faces. Three publicly accessible datasets (Arrest Records Database, VIP-Attribute Dataset, and Illinois DOC dataset) including pictures of both inmates and Hollywood celebrities were used to create the front-facing photos. The pictures could be blurry, irregular, or even have titles. A technique known as StyleGan is used to make them look identical. The face is then vertically aligned using a face landmark detection model called DLIB 68, and the background is blurred to isolate the face. The pre-trained model's whole network of completely linked layers is added, and the result is the person's BMI. The existing methodology differs significantly from the current system in that it makes use of pre-trained models like Inception-v3, VGG-Face, which employs computer vision to improve performance and shorten training time.*

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

1.INTRODUCTION

Body Mass Index (BMI) is a commonly used index that uses the ratio of a person's height to weight to reflect their general weight condition. Numerous aspects, including physical health, mental health, and popularity, have been linked to BMI. BMI calculations frequently call for precise measurements of height and weight, which entail labor-intensive manual labour. Any person's BMI (Body Mass Index) is an important sign of their health. If the person is underweight, normal, overweight, or obese, it is determined. Health continues to be one of the most overlooked factors. Even technology with many advantages has its downsides. It has made people more slothful, which has decreased their physical activity and resulted in a sedentary lifestyle and an increase in BMI, both of which are harmful to their health and raise the risk of chronic diseases. The likelihood of acquiring cardiovascular and other hazardous diseases increases with increasing BMI. On the other hand, some people struggle with issues like inadequacies and malnutrition. There are primarily four classifications based on BMI values: underweight (BMI <18.5),normal(18.5<BMI≤25),overweight(25<BMI<30), and obese(30<BMI), BMI can therefore assist a person in keeping track of their health.

A person can be learned numerous things just by looking at their face. Recent research has demonstrated a significant relationship between a person's BMI and their facial features. People with thin faces are likely to have lower BMIs, and vice versa. Obese people typically have bigger middle and lower facial features. If the person does not have a measuring device and a scale, calculating BMI can be challenging. Deep learning has made tremendous strides recently, enabling models to extract useful information from photos. These techniques allow us to extrapolate the BMI from human faces. Therefore, we have suggested a method to predict BMI from human faces in this study. This technique might make it easier for health insurance firms to keep track of their clients' medical histories. Additionally, the government might monitor the health statistics of a certain area and create laws in accordance with them.

2. OBJECTIVES

The proposed system's goals are as follows:

• To improve image quality by pre-processing the inconsistent images in the dataset.

• To align the face vertically when the image is tilted.

• To predict BMI by extracting facial traits from images.

• To use deep learning to predict Body Mass Index from previously pre-processed facial images.

3. LITERATURE SURVEY

1.''A computational approach to body mass index prediction from face images" by Lingyun Wen and Guodong Guo (2013): In this study, the BMI was determined computationally. By employing the Active Shape Model to extract facial landmarks from facial images, the authors were able to extract seven facial traits. These seven characteristics include ES (Eye Size), CJWR

(Cheek to Jaw Width Ratio), PAR (Perimeter to Area Ratio), WHR (Width to Upper Facial Height Ratio), FW/FH (Lower Face to Face Height Ratio), and MEH (Mean Eyebrow height) are all measurements of facial proportions. The regression issue was then solved using the Support Vector Regressor (SVR), Least Square Estimation, and Gaussian Process. They evaluated and trained using the Morph II dataset. SVR provided the greatest outcomes for both sets of data, according to the results. Barret al proposed the estimation of Facial BMI (fBMI) from facial measurements using a similar method. For evaluation, there was a stronger association between fBMI and BMI for the normal and overweight categories but a weaker correlation for the underweight and obese groups. Even if the results are significant, only facial landmarks are taken into account when extracting features. Additional advancements can be made by for evaluation, there was a stronger association between fBMI and BMI for the normal and overweight categories but a weaker correlation for the underweight and obese groups. Even if the results are significant, only facial landmarks are taken into account when extracting features.

2."Face-to-BMI: Using Computer Vision to infer Body Mass Index on Social Media" by E. Kocabey et al.(2015) : To predict a person's BMI from their social media photographs, Kocabey et al suggested a computer vision technique. Images were taken from the VisualBMI Project. They had employed 4206 facial photos on the VGG-Net and VGGFace models for deep feature extraction. If BMI declines, they have employed a support vector regression model with epsilon. The performance of VGG-Faces was superior to that of VGG-Net. The VGG-Face model's test set yielded Pearson correlation coefficients for the Male, Female, and Overall categories of 0.71, 0.57, and 0.65, respectively. Additionally, they showed predictions between humans and machines, showing that when it came to BMI categories with lower values, humans outperformed the machines.

3."A novel method to estimate Height, Weight and Body Mass Index from face images" by Ankur Haritosh et al. (2019): This study proposed an entirely novel approach for calculating BMI, height, and weight using facial photographs. They made use of 982 images from the Reddit HWBMI dataset and 4206 images from the VisualBMI project. The photos are cropped to 256256 after the Voila Jones Face Detection algorithm has been used. These images are provided to the 3-layered ANN model after the feature extractor model extracts high-level features from them. The MAE for BMI using XceptionNet was 4.1 and 3.8, respectively, using the Reddit HWBMI dataset and Face to BMI dataset. On the Reddit HWBMI dataset, the MAE was 0.073 for height provided by VGG-Face and 13.29 for weight provided by the XceptionNet model.

4."BMI and WHR Are Reflected in Female Facial Shape and Texture: A Geometric Morphometric Image Analysis" by Christine Mayer et al. (2017): In order to determine the association between body mass index (BMI) and waist to hip ratio (WHR) and facial form and texture, this study developed a statistical methodology. Using the Windows programme TPSDig, the authors highlighted 119 anatomical landmarks and semi-landmarks. They determined the precise placements of semi-landmark using a sliding landmark technique. Their analysis included 49 standardised pictures of women with BMIs between 17.0 and 35.4 and WHRs between 0.66 and 0.82. The contour of the face is represented by the Procrustes shape coordinates, and its texture is represented by the RGB values of the standard photos. The desired associations were evaluated using the multivariate linear regression method. Compared to WHR, the BMI was more predictable from face characteristics, with 25% of the variation coming from facial shape and 3–10% from textures.

5."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.

6. "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 pre-trained CNN models including VGG-19, ResNet, DenseNet, 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 pretrained models were employed. Pretrained models outperformed the end-to-end CNN model to some extent.

4. METHODOLOGY

The proposed system analyses face features to estimate BMI using the Python CNN (convolution neural networks) technique. CNN will use a picture as its input, extract the facial features from it, and then estimate BMI using those features.

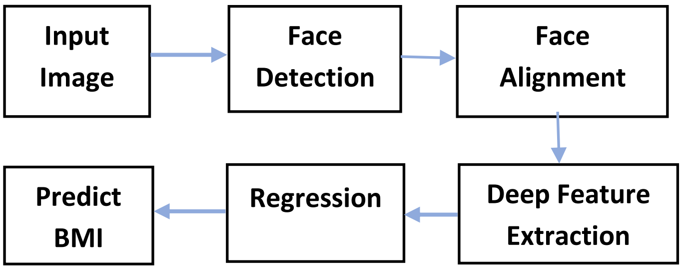

Figure 1: Flow Diagram

1.Input Image

The front-facing image from the dataset is used as the input and published to the application.

2.Face Detection

The facial detection CV2 library and BMI detection CNN model are loaded by the face detection module. When a human face is detected in an uploaded image, facial features are added to the CNN model to forecast BMI.

3.Aligning the Face

The task of this module is to analyse the face characteristics. If the input is blurry or skewed, for example, the image is zoomed in and aligned for pre-processing, which is carried out using the StyleGan technique and the DLIB 68 landmark model.

4.Deep Feature Extraction

This module describes how to provide input data to a pre-trained CNN and then get the appropriate activation values from the fully connected layer, which is typically at the network's end, or from the multiple pooling layers, which are present at various levels. Regression is used during deep feature extraction itself to simplify the output produced.

Regression:

It is primarily used to predict outcomes, anticipate future events, model time series, and identify the causal relationships between variables. Regression involves creating a graph between the variables that best fits the given data points. The machine learning model can then make predictions about the data using this plot.

5.Predicting the BMI

The face is extracted from the provided input image in this final module, and the features are analysed as indicated in the earlier modules to finally forecast the BMI. The estimated BMI can be used to rapidly determine if a particular individual is overweight or underweight.

5. ARCHITECTURE

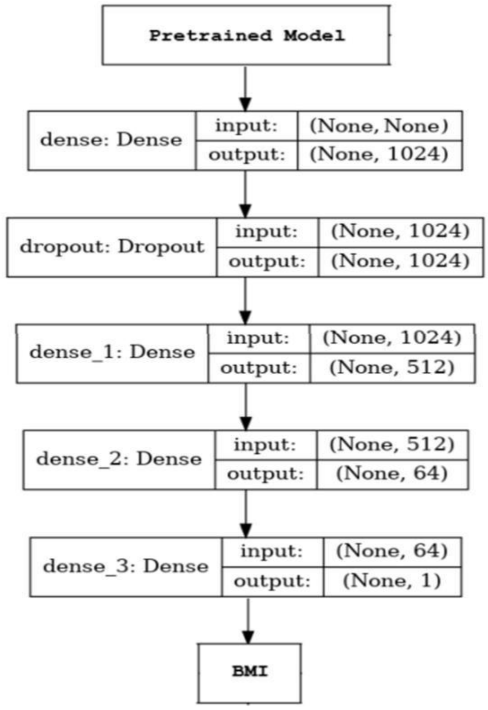

Figure 2: Model architecture for the project

- All pre-trained models employ the fully linked layers at the end. In Figure 2, the layers that are applied in the end are depicted.
- We carry out Global Average Pooling prior to feeding the output of the pre-trained model into the fully connected layers. The model architecture presented in the above graphic includes one dropout layer with a dropout of 50% to prevent overfitting.
- Additionally, the Gaussian Error Linear Unit (Gelu) activation function, shown in Figure 2 of the Model Architecture, combines the characteristics of the RELU activation function, Dropout, and Zoneout.
- As a result, it is employed in the architectural model since it tends to generalise better when there is more noise in the data. The prototype can be improved if a significantly larger dataset is used.
- The layers typically pick up advanced features as the architecture advances towards the output due to the fact that layers close to the input in deep convolutional networks acquire fundamental properties like edges and corners. So that the pre-trained model can extract more characteristics 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.

6. RESULTS

The advantages of the proposed system clearly outweigh the design, model and therefore the challenges of the existing system. Previously the faces taken as input are not aligned to the centre, but in the proposed system any titled, blur or distorted, inconsistent images can also be classified thus gradually reducing time and enhancing performance. Active shape model was largely used in the pre existing system, but this has been eliminated by using preprocessing techniques such as StyleGAN technique which makes the inconsistent images similar, then DLIB 68 Landmark model comes into picture, which aligns, zooms in and blurs the surroundings while focusing on the face. The models trained for the prediction of BMI in the proposed system which are VGG-Face,Inception-v3,VG-19 and Xception give the proposed system a huge advantage over the existing system since the mentioned models use Convolutional Neural Networks with numerous layers, while each being unique and support different functionality by applying the latest developments in deep learning therefore helping in efficient calculation and better accuracy of the individual's BMI.

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 found that those with higher BMIs are more likely to experience health problems. It has been discovered that there is a significant correlation between BMI and a person's face. Therefore, a method for predicting BMI from facial photos using deep learning is suggested. The Python CNN (convolution neural networks) technique is used to analyze the facial features and determine BMI. Before estimating BMI based on those aspects, CNN will utilize a photo as its input and extract the face characteristics from that input. The BMI detection technique is used to centre the faces and pre-process the facial data.

The technique will be used in subsequent research to simulate population-level obesity rates using images from social media profiles. According to preliminary findings, a significant number of Instagram profile pictures represent variances in BMI that are both geographical and demographical.

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