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BMI Prediction Using Facial Features with Deep Learning Techniques

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Abstract: Body Mass Index (BMI) is a simple measure that links a person's weight to their height. It's widely used to assess health levels and risks. But measuring height and weight can be inconvenient. Or not always possible. In this study, we explore an alternative—predicting BMI from facial images. One such approach involves leveraging facial features extracted from images to predict BMI, eliminating the need for direct physical measurements.

This study presents a deep learning-based system that utilizes Convolutional Neural Networks (CNNs), particularly ResNet50 architecture, to analyze facial images and predict BMI through a regression layer. The model is trained on pre-processed facial datasets, using Haar cascade classifiers for face detection and standardization. Once the features are extracted, the system classifies the estimated BMI into standard health categories such as underweight, normal, overweight, or obese.

This approach offers a non-intrusive, practical alternative for BMI estimation, particularly useful in healthcare applications, mobile health platforms, and wellness tools. Using Convolutional Neural Networks (CNNs) and regression models, we created a system that takes in a face and gives an estimated BMI. No physical measurements. Just one photo. This approach can help in healthcare, social platforms, or any scenario where quick BMI estimation is useful.

Keywords: BMI, CNN, ResNet, facial features, image-based prediction, regression

I. INTRODUCTION

Body Mass Index (BMI) has long served as a reliable metric for evaluating an individual's health. It helps classify people as underweight, normal, overweight, or obese. The BMI concept, introduced by Lambert Adolphe Jacques Quetelet, is based on a person's height and weight. Despite its inability to distinguish between muscle and fat, BMI remains a practical tool to gauge obesity levels.

Today, one of the overlooked health challenges is sedentary lifestyles influenced by modern conveniences, which often leads to higher BMI levels.

Facial characteristics can reveal important insights. Recent developments suggest a notable association between BMI and facial structure. Thin faces generally reflect lower BMI values, while fuller features suggest a higher BMI. However, without accurate height and weight measurements, calculating BMI is challenging. Deep learning enables models to extract valuable patterns from visual data, such as faces. This paper introduces a deep learning-based method to estimate BMI using facial images, eliminating the need for manual measurements.

A. Scope of BMI using Facial Features

BMI is commonly derived by dividing weight by the square of the height. However, obtaining these physical values isn't always possible. For example, individuals who are immobile or lack access to measuring equipment may be unable to calculate their BMI. Hence, researchers have turned to facial features as a potential proxy. This method aims to offer a non-invasive, practical solution for estimating BMI in scenarios where traditional methods fall short.

Facial structure elements like cheekbone width, jawline definition, eyebrow spacing, and ear length can be processed using machine learning to estimate BMI. These facial indicators have shown significant correlation with BMI. Although this area is still evolving, it has demonstrated potential. A major challenge lies in acquiring large, diverse image datasets due to privacy concerns, which impacts model training and generalization.

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II. RELATED WORK

As obesity continues to rise globally, the need for accessible self-assessment health tools has increased. Many researchers have investigated the use of AI and deep learning to estimate BMI from facial images. For instance, one study compared five deep learning models: VGG, ResNet50, DenseNet, MobileNet, and LightCNN.

In another approach, a multi-task convolutional neural network was built to estimate BMI and used SMTP protocol to email results to healthcare professionals. This method trained on multiple parameters such as age, gender, and facial data.

The ResNet50 architecture, a deep residual network, has also been used to predict demographic details like age and gender using facial images. A deeper version, ResNet-152, was trained on ImageNet for improved accuracy.

Public images from online platforms were also employed to build a two-stage BMI prediction system—one stage for feature extraction and another for regression modeling.

III. PROPOSED MODEL

This research presents a Convolutional Neural Network (CNN)-based model for estimating BMI using facial images. The system analyzes facial traits to categorize individuals into BMI groups: underweight, healthy, overweight, or obese. The model is trained and validated using the ImageNet dataset, which is widely used for image classification tasks.

For facial detection, a Haar cascade classifier—a pre-trained algorithm—is employed to isolate and crop the face area to the required dimensions of (224, 224, 8). This preprocessing step ensures consistent input for the CNN model.

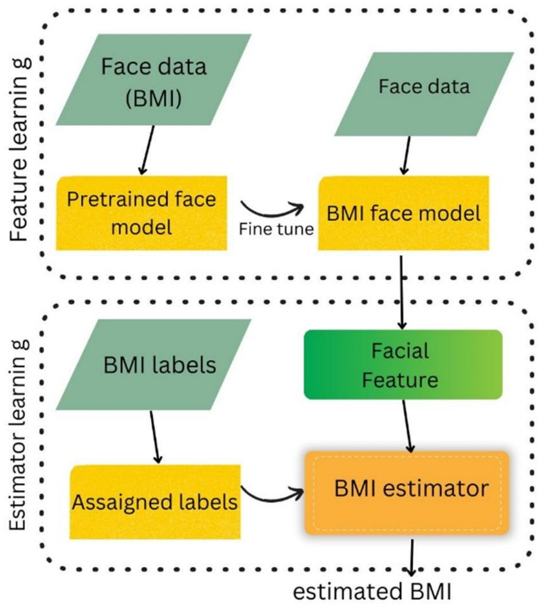

Fig: Proposed Model block diagram

IV. SYSTEM ANALYSIS

Python programming language is used to build this model where libraries like Tensorflow, Keras, OpenCV, Numpy, Pandas, Tkinter etc... are used.

The model is developed in Python using various libraries including TensorFlow, Keras, OpenCV, NumPy, Pandas, and Tkinter.

A. Tensor flow

Keras is used for building and experimenting with deep neural networks. It works on backends like TensorFlow, Theano, or CNTK and supports easy layer customization.

B. CNN

CNNs are a type of artificial neural network tailored for visual pattern recognition. They rely on convolution operations in at least one layer to process image data.

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C. ResNet50
Introduced in 2015, ResNet solves the vanishing gradient issue and allows deeper architectures. The ResNet50 variant includes 50 layers and employs softmax activation, setting benchmarks in large-scale visual tasks.

D. Haar Cascade
This classifier detects objects in visual data based on features like edges and corners. Though effective, it can be resource-intensive.

E. Activation Functions
These define neuron responses to inputs.
- *Softmax:* Often used for multi-class classification, converting raw outputs into probability values.
- ReLU: Introduces non-linearity, widely used in CNN models due to its efficiency.

V. IMPLEMENTATION

A. Importing the required packages
Fig: 1&2 is a screenshot of the code importing the required libraries.

```
mo.py
  from Model import get_model
  import cv2
  import numpy as np
```

Fig: Importing libraries for image analysis

```
Model.py

from tensorflow.python.keras.models import Model
from tensorflow.python.keras.applications import ResNet50
from tensorflow.python.keras.layers import Dense
```

Fig: Importing libraries for Deep learning models

To develop the prediction model, we utilized TensorFlow Keras and leveraged its pre-existing deep learning architectures. The ResNet50 model, a widely used residual neural network, was imported and adapted for image-based analysis. Additionally, Dense layers were included to enhance the model's learning and output capabilities.

For facial feature extraction, we used the NumPy and OpenCV (cv2) libraries. These tools helped in identifying and isolating the face from the uploaded image. The detected face was then resized to a standard input shape of (224, 224, 8), making it suitable for the CNN model to process and extract the necessary features for BMI prediction.

```
age_model = ResNet50(
    # pre trained model
    include_top=False,
    weights='imagenet',
    input_shape=(224,224, 3),
    pooling='avg'
)

prediction = Dense(units=101,
                   kernel_initializer='he_normal',
                   use_bias=False,
                   activation='softmax',
                   name='pred_age')(age_model.output)

age_model = Model(inputs=age_model.input, outputs=prediction)
```

Fig: Creating Model

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To build the prediction model, we utilized the ResNet50 architecture with pre-trained weights from the ImageNet dataset. The input image was resized to dimensions (224, 224, 3) and passed through the network, where average pooling was applied to reduce the dimensionality of the feature maps.

The resulting output was then connected to a Dense layer consisting of 101 units, initialized using the “he_normal” initializer. A Softmax activation function was applied to generate probability distributions across multiple classes.

Using the Model class from Keras, a new model was defined with the original input from ResNet50 (referred to as age_model) and the output of the newly added Dense layer. This setup repurposes the base ResNet model for our specific prediction task.

```
def get_model(ignore_age_weights=False):

    base_model = get_age_model()
    if not ignore_age_weights:
        base_model.load_weights('age_only_resnet50_weights.061-3.300-4.410.hdf5')
        print('Loaded weights from age classifier')
    else:
        print("not require")
    last_hidden_layer = base_model.get_layer(index=-2)

    base_model = Model(
        inputs=base_model.input,
        outputs=last_hidden_layer.output)
    prediction = Dense(1, kernel_initializer='normal')(base_model.output)

    model = Model(inputs=base_model.input, outputs=prediction)
    return model
```

Fig: Building the prediction model

Further, the base age_model was used to construct another model, where the input remained the same, but the output was taken from its final hidden layer. A Dense layer with a single unit was then added to produce the BMI prediction. The final model combines the original ResNet input with the new output layer, resulting in a BMI estimator based on facial features.

VI. RESULTS

BMI is considered a measure of body fat based on a person's height and weight. It can serve as a screening tool. BMI may also be used to diagnose a variety of health issues.

Based on BMI, a person is classified as follows:

1) Underweight: BMI < 18.5
2) Healthy Weight: 18.5 ≤ BMI < 24.9
3) Overweight: 25 ≤ BMI < 29.9
4) Obese: BMI ≥ 30

BMI values are used to classify individuals into various categories based on their health status.

Fig: UI of landing page

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The interface functions in the following steps:

- First, click on the "Generate and Load BMI & Face Detection Model" button. This action initializes and loads the pre-trained CNN model
- Next, to input an image, click on "Upload Image" and select a photo from your local system. (Note: The image should ideally contain only one individual for accurate BMI prediction.)
- After uploading the image, click on "Run Face and BMI Detection Algorithm" to start the prediction process
- Once completed, the system displays the output, including the estimated BMI value and its corresponding category.

For example, one image produced a BMI of 20.70 (Healthy Weight), and another produced 17.71 (Underweight). The interface allows simple execution and interpretation of BMI predictions from facial images.

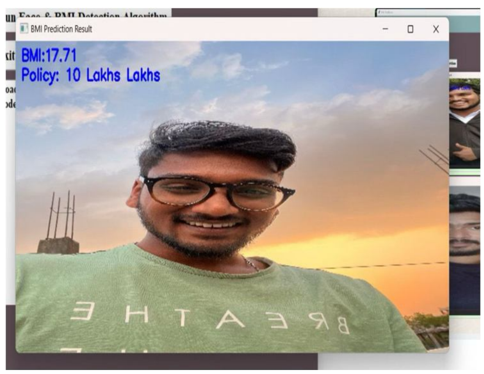

Fig: Output on UI screen

The BMI of the above images are 20.70 and 17.71 respectively classifying the two pictures as Healthy Weight and Underweight.

VII. CONCLUSION

The findings highlight a measurable relationship between facial structure and BMI. Those with elevated BMI are at greater health risk. The system does not require full-body images—just a face is enough. The process involves feature extraction, model training, and classification. No significant gender bias was found, though performance may still be improved.

Main challenges include the need for large datasets and the difficulty in predicting multiple individuals in a single image. Future models can benefit from higher diversity in training data to enhance robustness and accuracy. The model also struggles with translating 2D facial data into precise BMI values.

VIII. FUTURE SCOPE

Since not everyone has access to or knowledge of their weight and height, facial BMI prediction provides a convenient alternative. This approach can be implemented into mobile and health applications to provide real-time BMI assessments. The model can also help suggest diet plans based on BMI and be integrated into medical reporting systems. A mobile version could further enhance accessibility and practicality.

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