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Predictive analytics of BMI (body mass index) using captured image analysis by convolutional neural network

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ABSTRACT

Body Mass Index (BMI) is a measurement of one's weight concerning his/her height. It is more an indicator of measurement of one's total body fat. BMI is very important as it is widely measuring in estimating health conditions. It is supposed that we have chances of having longer and healthier life with a healthy BMI. Identifying and classifying the BMI range with image analysis can help people predict credibility, control their BMI, and maintain a healthier life. Image analysis makes this very simple to classify the BMI range by analyzing the image using a deep learning algorithm named Convolutional Neural Networks. In this work, the user has to upload the image of a person for image processing. The training algorithm categorises it as undernourishment, healthy bmi, or high bmi. The input picture has to be a colourful image in the format .jpg, .jpeg, .png. This work can identify the BMI range successfully, and we got an accuracy of 82% for the model. The input picture is categorised, and the result will fall into those three previously specified classes. This work proposes a reliable depiction that is also user-friendly, allowing anybody to effortlessly check their BMI. Therefore, based on a diagnosis of BMI through image classification, one can easily follow corresponding diet procedures and maintain a healthy BMI, making it easy and supportive for the nutritionists to analyze and diagnose a patient's health status.

Keywords: Convolutional neural networks, body mass index, Image Data Generator, Support Vector Regression.

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INTRODUCTION

According to the NHI (National Health Institutes), the BMI (body mass index) estimates an individual's body fat. Make a weight division (in pounds) into squared height to measure BMI, then multiply the sum by 703. This equation can measure kilograms weight and meters altitude, but no transformation factor is required.

An elevated BMI is associated with a high amount of weight and excess body fat. Causing a lot because overweight (calories) absorbed in nutrition is higher than the energy we obtain by movement. An attributed the reduction of plant-based foods is associated with higher body weight because these foods have lower power than other foods. The excessive consumption of carbs and calories, one on each hand, is associated with an increased BMI due to the extremely greater volume of certain commodities than fruit and veggies [1].

The BMI system, irrespective of gender, is precisely calculated in kilograms in the aged. The measurement uses kilograms and meters. A simplified BMI scheme, utilizing kgs and meters, is assumed to be the standard BMI system. For 20 or older adults, the BMI definition intends. A BMI is to be defined in 18-25, 25-30, 30-35, and 35-40, respectively. During the day before tea, BMI should preferably evaluate when it is the most precise person's weight.

In several investigations, the BMI was utilizing to measure which features an elegant in several diseases [2,3]. The data suggests that high BMIs have been relating to certain cancers for both males and females (such as breast cancer, colon cancer, thyroid cancer, etc.) [4,5]. The potential risk of unstable coronary artery disease and ischemic stroke in patients is well-defined by BMI [6] .

Image classification is when an image is choosing, and a class specified the chance that the input is a class. A CNN operates by excluding image characteristics. This removes the need to extract manual functions. The network is training on some frames. Artificial neural technology is a significant factor of a deep learner for the study of the images. For image analysis and categorization CNN performs exceptionally effectively. The method employs machine learning to ensure the maximum precision of the model.

The remaining of the paper is configuring as the related work is discussing in Section II. The describing the data collection process is specifying in Section III. Section IV make available examination of the proposed procedure. Section V presents the assessment findings with real-world data in our methodology. Section VI concludes the paper and highlights our future directions.

RELATED WORK

A complex feature extraction system of BMI proposed utilizing VGG in conjunction with the SVR (Support Vector Regression) [7]. Pearson's and correlation for the male, female and combined resulted from observations in the graphical BMI dataset accumulated of the web. An edge CNN completes by substituting the layer throughout the last completely connected one ResNet channel and retrieving a smooth L1 loss [8,9].

In insulin resistance utilizes to demonstrate the probability of obesity [10]. A specific and effective path recommend the traditional approach to achieve candidates' fitness levels, as discussed in [5]. The suitable technique is time-consuming and complicated. Used to measure men's cholesterol levels are several methods such as Body Adiposity Index (BAI) and atmospheric pressure weights. The use of such a BMI depiction emphasis the usage of the techniques of image processing.

Characterizing women's obesity distributions focused on the abdomen and waist parameters [11]. Interdependence of crossover lipid enhancement seen between quantities of mass and gestational weight gain in the reproductive organs of females [12]. Also include the abdominal ratio and hip ratio were often evaluating. According to an investigation of the human appearance and gastrointestinal moisture, a multi-diameter, membrane flux, BMI, and lifetime can be properly estimating for quantities of intra-abdominal fat and intra-muscular abdominal fat association [13].

In some facial features have been examining in the assessment of human wellbeing [2]. They find that facial characteristics such as complexion hardness, physical appearance, and reflectivity significantly correlate with fat accumulation, while facial form with the perception of fitness negatively correlates.

To analyze the assessment data, a polynomial regression model is using. The need for real body metrics for the forecast of certain soft biometric systems, including gender and weight (provided in CAESAR 1D) is mentioned [14]. A tool for automated extraction of geometric characteristics from 3D facial data concerning weight vector. BMIs were measure in facial images obtained on a Platform of digital media. Use VGG-Net and VGG-Face pre-trained models to feature extraction before using a supportive form of vector regression to forecast BMI [15].

MATERIAL AND METHOD

CNN (Convolutional neural networks) is a deep learning subfield that is being used to evaluate visual information. It is employed as a classifier, which aided us in processing and categorizing the pictures. Different categorization approaches include the RF (random forest), DT (decision tree), and so on. However, we chose the CNN because it employs a backpropagation approach that incorporates the procedure far more efficient when compared with other methods that take into account the diversity of image input. The reliability of the model largely depends on the features retrieved from the images.

Different data enhance techniques were applied including rotational range, width shift range, height shape range, shear range, zoom range, horizontal flop, and fill mode to extend the direction and color increase of the input dataset.

Image classification is a technique of segmenting images into different categories based on the extraction of the feature. The method can remove features. The key principle of CNN is that it uses image convolution and other filters to produce invariant functions transferred to the next level. The next layer features are mixed with various filters to provide more invariant and abstract features, and the procedure proceeds until the end feature/output is consistent in conclusions. Image characteristics include intensity values, pixels, edges, boundaries, areas of key points, patterns, and so on. The extracted features are formed via image classification, which provided as a foundation for distinguishing extracting or learning the features from the data set without the need for person involvement. Since our data consist of categorical cross-entropy, used the SoftMax activation feature, absolute cross-entropy loss feature, and the 0.00001 learning rate for the most dominant and efficient Adam optimizer. The proposed network may automatically retrieve from a source image and train at the classifier specified by the Adam optimizer. Because one image of a categorical label can readily be discriminated from some other, the method is efficient and robust.

RESULT ANALYSIS

With high reliability and stable outcomes, ML (Machine Learning) is becoming a common subset of Deep learning. A very good method of ML is developing convolutions neural network to identify images (CNN). The Python Kera’s library makes making CNN very simple.

Data loading and data augmenting

The initial phase we took was to upload the dataset, which had been carefully gathered and structured from multiple online sites. So, we ingested the collection by using Python library module Kera’s Kera’s, and then used the Image data generating module to conduct various image processing techniques to extend the source dataset. In addition, we separated the data into training and testing sets and determined the labelled values of several classes.

Layers and structure of the model

Sequential is the model method used. Since in Kera’s, it is one of the simplest ways to develop a model. The proposed method introduced various layers such as Maxpooling2D, Conv2D, Dropout, Flatten and Dense layers with the add feature.

Conv2D and Maxpooling2D layers are the first two layers. These are classified as coevolutionary layers that handle input images and are regarded as 2-dynamic matrices. In the convolution layer, the data is replaced by a calculated value from the pixels protected by a data replacement for all (1) pixels, and pooling layers minimize the spatial output size by substituting the values within the kernel with those values. The term "dropout" refers to falling units into a neural network (which is both concealed and recognizable) to remove the overfitting. A flattening layer is between the Conv2D layers and the thick layer, connecting the convolution to dense layers.

Figure 1. Layers and structure of the model

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_50 (Conv2D)           (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d_50 (MaxPooling (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_51 (Conv2D)           (None, 31, 31, 32)        9248
_________________________________________________________________
max_pooling2d_51 (MaxPooling (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_52 (Conv2D)           (None, 15, 15, 64)        18496
_________________________________________________________________
max_pooling2d_52 (MaxPooling (None, 7, 7, 64)          0
_________________________________________________________________
dropout_22 (Dropout)         (None, 7, 7, 64)          0
_________________________________________________________________
flatten_20 (Flatten)         (None, 3136)              0
_________________________________________________________________
dense_55 (Dense)             (None, 128)               401536
_________________________________________________________________
dense_56 (Dense)             (None, 3)                 387
=================================================================
Total params: 430,563
Trainable params: 430,563
Non-trainable params: 0
```

Activation functions

ReLU has been added to the original layers which yields 0 if it obtains any undesirable feedback, but returns this value for a positive value x. The action function has the feature of activation as SoftMax, which provides an output value of up to 1. The model then supports its estimation of the most probable alternative.

Validating the model

Using a 0.000001 learning Adam Optimizer since Adam is a substitution algorithm for optimizing stochastic gradient descent in deep learning models. This technique combines the most basic features of the Ada Grad and RMS Prop algorithms to provide a considerably smaller optimization approach for noisy issues. Cross-entropy was used as a loss function as we have jointly excluded the predictive classes of concern and the most available classification option. A lower score shows that the formula works well.

Used the "precision" to perceive the validity score in the model train to make matters much easier to read.

Training the model

The training data used consisting of 4000 images captured from the front of the theme of each specific personality. The BMI of every exercise calculates the fitness level of the person (BMI is weight in kg divided by the squared height in meters) The classifier is trained by utilizing fit generator () function with the parameters: train X, train y, validation set, stages per epoch, and the number of iterations. The classification is performed across 500 iterations, with 4 show the correct and 16 steps per epoch. With 500 iterations of training, the classifier had an estimated precision of 82 percent on our testing data. Then, we created a plot to visualize the model's fit to a validation data, and we found a decent fit plot (nearly coinciding). To properly evaluate the system, the confusion matrix and categorization results of the proposed method were discovered utilizing performance measures was shown in Table 1.

Table 1: Val_loss Vs Val_acc

Epochs	Loss	acc	Val_loss	Val_acc
1/500	1.0987	0.3327	1.0979	0.3774
2/500	1.0995	0.319	1.0977	0.3585
3/500	1.0977	0.368	1.0974	0.4151
4/500	1.0972	0.3777	1.0972	0.4151
5/500	1.0958	0.3581	1.0971	0.3208
6/500	1.0971	0.3591	1.097	0.2642
7/500	1.0945	0.357	1.0969	0.2642
8/500	1.095	0.3434	1.0968	0.2642
9/500	1.0938	0.3522	1.0966	0.2642
10/500	1.0942	0.3405	1.0965	0.2642
11/500	1.0916	0.3406	1.0965	0.2642
12/500	1.0918	0.3541	1.096	0.2642
13/500	1.0917	0.3396	1.0958	0.2642
14/500	1.0904	0.3503	1.0956	0.2642
15/500	1.0905	0.3415	1.095	0.2642
16/500	1.0907	0.3396	1.0945	0.2642
17/500	1.0901	0.3396	1.094	0.2642
18/500	1.0895	0.3338	1.0932	0.2642
19/500	1.0871	0.3454	1.0922	0.2642
20/500	1.088	0.3434	1.0914	0.2642

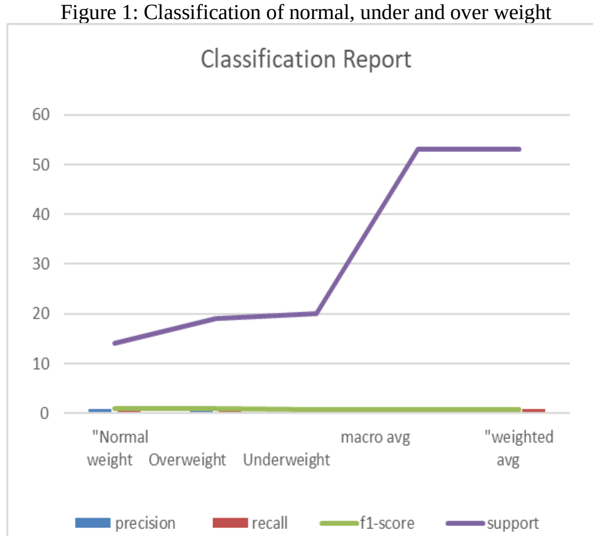
BMI Prediction

The proposed CNN model was showing to be useful for highly accurate BMI prediction. Validation set prediction error after 32 epochs hit a minimum (Table 2).

Table 2: Classification report of different weights

Weight	Precision	Recall	F1-score	Support
Normal weight	0.76	0.93	0.84	14
Overweight	0.84	0.84	0.84	19
Underweight	0.82	0.7	0.76	20
Macro avg	0.81	0.82	0.81	53
weighted avg	0.81	0.81	0.81	53

Figure 1: Classification of normal, under and over weight



A confusion matrix describes and visualizes the algorithm classifier's performance and provides insight into What's inconsistent with the model. The model is sensitive and precise, determined utilizing the confusion matrix. The results of measured classification were shown in figure 2.

SENSITIVITY=(TP)/(TP+FN)

SPECIFICITY=(TN)/(TN+FP)

where TP: True positive, TN: True negative, FP: False positive, and FN: False-negative.

Confusion Matrix- [13 0 1] [1 16 2] [3 3 14]]

Accuracy: 81%, Sensitivity: 92.8%, Specificity: 88.2%

PERFORMANCE ANALYSIS

Using CNN, we achieved accuracy for image data of 3 categories together at 82%, where the previous model has an accuracy up to 61%, which built using facial photographs. Our model predicts output for categorical data. The model dataset consists of 3 categories under the BMI scale as underweight, normal weight and overweight.

Figure 2: Measures of classification

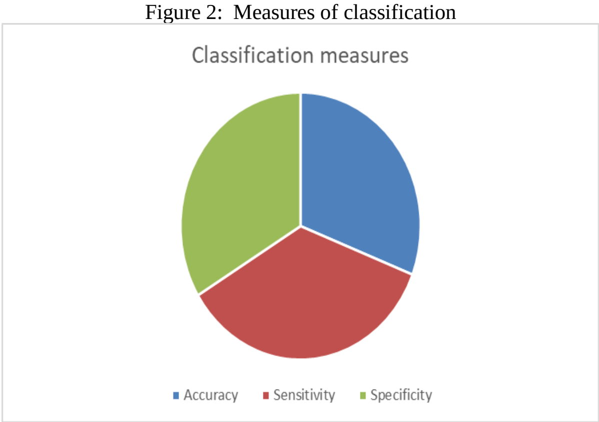
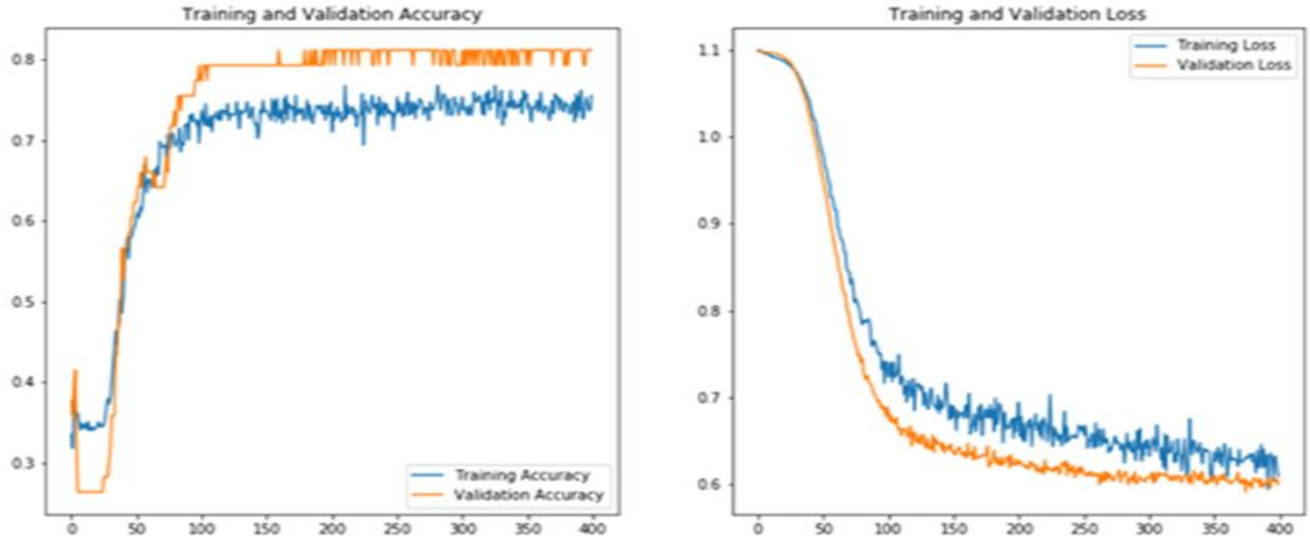


Figure 3: Training examples accuracy Vs. Loss functions



Based on the graphs above, we can analyze the performance accuracy as the training and validation metrics are nearly fitting the data. Model trains with a computed value of 0.00001 and iterations at a range of 400. To enlarge our dataset, we used Image Data Generator to generate different features from a single image. The method has been training by implementing different neural network layers for instance Maxpooling 2D, Convolutional 2D and several data augmentation methods to generate multiple image frames.

CONCLUSION

The proposed method for this study was to use image processing techniques to estimate people's BMI. To achieve this objective, the following prerequisites have to be met: Using only a digital camera, image respondents, turn the captured image into a silhouette, and determine the elevation of the object, determine the size of the body (the difference between the highest pixel and the lowermost pixel), receive the volume occupied by the silhouette (i.e., number of pixels that the shape contains) by image processing methods within and, the subsequent calculation of BMI utilizing the volume and height from above. Also deceptive is the established BMI standardized method concerning the role of body fat mass on mortality rates. BMI does not capture the function of fat distribution in predicting major medical morbidities and probability of mortality. Numerous co-morbidities, problems with diet, gender, ethnicity, family-determined mortality effectors of medically significant length. Some BMI categories are spending, and the anticipated fat accumulation is likely to dramatically influence how BMI data are interpreted, particularly concerning the death rate.

FUTURE ENHANCEMENT

In future work, analyzing the risk prediction of other diseases is using the level of obesity rates. Demographic differences in BMI are reflecting in large amounts of pictures. BMI's roles with patients with thyroid vary, such as hypothyroid, hyperthyroid, and other thyroid forms.

CONFLICT OF INTEREST

None.

ETHICAL APPROVAL

Not Applicable.

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