Prediction of Body Mass Index from Facial Features of Females and Males

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Abstract

Human obesity has become a global epidemic. Body mass index (BMI) is clinically useful data for the diagnosis of overall adiposity. The purpose of this study was to identify normal and overweight patients based on facial characteristics extracted from subject image data, irrespective of the measurement of weight and height. In this paper, we propose a prediction method for normal and overweight from morphological facial characteristics that are associated with overweight and normal BMI statuses. A total of 1244 subjects participated in this study. The subjects were divided into 6 groups based on age- and gender-specific differences. The area under the receiver operating characteristics curve (AUC) and kappa of the prediction model ranged from 0.760 to 0.931, and from 0.401 to 0.586, respectively, for all groups, except for the group comprising females aged ≥61 years. Statistical analysis revealed many features that were significantly different between overweight and normal in the 6 groups. Furthermore, compact and useful feature sets were identified for BMI prediction using facial features in gender- and age-specific groups. We identified a relationship between facial morphology and BMI status, and the possibility of predicting the BMI status of individuals. Our results will facilitate the development of improved applications for age- and gender-specific groups in the fields of adiposity, facial recognition, and medicine.

Keywords: *Classification, Body mass index (BMI), Machine learning, Relationship, Facial morphology*

1. Introduction

Body mass index (BMI) is an indicator of the degree of obesity of individuals. The BMI of patients with obesity-associated diseases is more important as a risk factor for health problems. Thus, BMI is clinically significant datum for medical therapy and disease prediction. BMI, invented by Lambert Adolphe Jacques Quetelet, is calculated from the height and weight of individuals [1]. The principal cut-off points for underweight (<18.50 kg/m^2), normal range (18.50–24.99 kg/m^2), overweight or pre-obese (25.00–29.99 kg/m^2), and obese (≥30.00 kg/m^2) have been set by the World Health Organization (WHO).

The prevalence of obesity is increasing worldwide. Obesity is associated with health problems, including hypertension, cardiovascular disease (CVD), dyslipidemia, breathlessness, type 2 diabetes, and insulin resistance [2], and is an important risk factor for mortality related to CVD and other chronic diseases [3-8]. Therefore, numerous studies have attempted to determine the relationship between BMI, obesity, and disease [9-15] in the research fields of genetics, medicine, and facial morphology [16-27]. The human face offers important clues for the diagnosis of diseases and genetic conditions [20, 28]. For example, in genetics, Medved and Percy [29] reported that Prader-Willi syndrome (PWS) is associated with diabetes and obesity, and patients with PWS exhibit a tendency toward narrow face, narrow nasal bridge, and almond-shaped eyes. Patients with obstructive sleep apnea (OSA), a risk factor for CVD, exhibit shorter maxilla and mandible [30, 31], and thus facial characteristics such as mandibular distance are used in OSA diagnosis [31]. Further, Tobin and Beales [32] suggested that facial characteristics of patients with Oral-facial-digital (OFD) type I syndrome include broad nasal bridge, buccal frenulum, lingual hamartomas, cleft palate, and hypertelorism. The facial features of patients with Bardet-Biedl syndrome (BBS) include small mandible, deep-set eyes, small cheek bones, small mouth, a flat nasal bridge with anteverted nares, thin upper lip, and long philtrum [32-34].

In our previous study [35], we used facial characteristics to classify normal and overweight female subjects. The study did not include male subjects. Furthermore, statistical analysis of facial characteristics between male and female and between age groups was not performed. In the present study, we focused on identifying normal and overweight in age- and gender-specific subject groups using facial features, and analyzed the differences between age groups and/or between gender groups in normal and overweight. The results from this study will provide better discriminatory characteristics for studies in obesity, facial morphology, face recognition, and forensic and medical sciences. Additionally, this method may be useful in developing alternative diagnosis methods for BMI status in telemedicine (U-healthcare), emergency medical service, and real-time monitoring of patients with chronic illnesses directly related to BMI.

2. Methods

2.1. Subjects and Data Acquisition

Frontal and profile images were acquired from 1244 subjects in various hospitals. To acquire photographs and weight and height information of subjects, we used a Nikon D700 with an 85-mm lens, a ruler, a color chart, and an LG-150 (G Tech International Co., Ltd). The BMI of each subject was calculated using the formula weight (kg)/height (m^2), and 86 features were extracted from profile, frontal, and eye photographs based on the feature points designated by a physician. The feature points in images, the extracted features, and brief descriptions are presented in Figure 1 and the Appendix Table which are quoted from our previous paper [35]. To set normal and overweight cut-off values, we used the Asia-Pacific region guidelines of WHO [36]: normal (BMI = 18.5–22.9 kg/m^2) and overweight (BMI $\geq$ 23 kg/m^2).

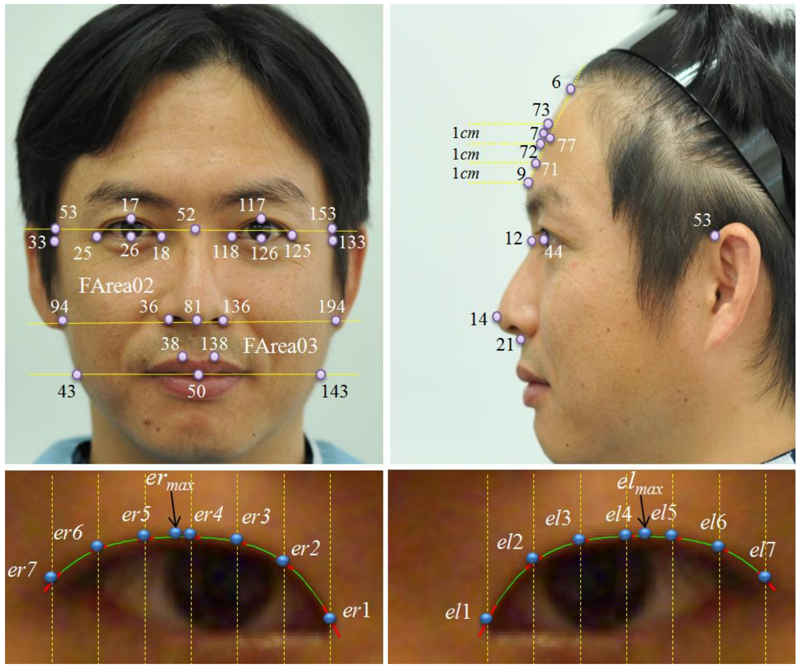

Figure 1. Feature Points in Frontal Photograph, Profile Photograph, Right Eye Photograph, and Left Eye Photograph

For age- and gender-specific analysis and classification, the full dataset was divided into 6 groups: Female-21-40 (women aged 21–40 years), Female-41-60 (women aged 41–60 years), Female-61-over (women aged ≥61 years), Male-21-40 (men aged 21–40 years), Male-41-60 (men aged 41–60 years), and Male-61-over (men aged ≥61 years). Detailed data and the basic statistics of each group are presented in Table 1.

Table 1. Basic statistics of subjects in the 6 groups. Data are expressed as mean (Std, standard deviation); N, total number of subjects in each group; BMI, body mass index.

Group	Normal			Overweight		
	N	Age (years)	BMI	N	Age (years)	BMI
Female-21-40	189	32.1 (5.64)	22.2 (2.97)	77	32.91 (5.29)	26.0 (2.75)
Female-41-60	193	50.0 (5.42)	23.6 (2.86)	229	50.31 (5.44)	25.6 (2.31)
Female-61-over	36	67.7 (6.37)	21.3 (1.15)	85	67.4 (4.51)	25.3 (1.71)
Male-21-40	54	30.7 (5.66)	21.2 (1.19)	90	32.5 (5.22)	25.6 (2.16)
Male-41-60	79	50.2 (6.11)	21.3 (1.13)	134	50.3 (5.55)	25.9 (2.16)
Male-61-over	24	67.1 (4.50)	21.4 (1.25)	54	67.5 (4.73)	25.4 (1.71)
Total	575	-	-	669	-	-

2.2. Experimental Design

For feature selection in each group, only features that exhibited a p-value less than 0.05 in an independent two-sample t-test were selected. Furthermore, only the selected features were used in classification experiments and statistical analysis.

Our experiments were carried out using 2 methods. In the first method, we applied normalization (ranging from 0 to 1) to the datasets of the 6 groups. In the second method, for superior classification performance, we applied normalization and discretization to the datasets of the 6 groups. Fayyad and Irani's MDL method [37] (Entropy-based multi-interval discretization) was used for discretization. The core of the discretization method is to discover the cut point to minimize the average entropy of the class. Let us assume that an example set S, a feature F, and a cut point T are given. The class information entropy of the partition derived from *E(F,T;S)* is given by:

$$E(F,T;S) = \frac{|S_1|}{|S|} Ent(S_1) + \frac{|S_2|}{|S|} Ent(S_2).$$

Discretization for *F* is decided by the cut point T_F, through minimization of the entropy function over all the candidate cut points [37, 38]. All experiments were carried out using the Naive Bayes classifier in the Waikato Environment for Knowledge Analysis (Weka) tool [39]. Naive Bayes estimates class-conditional probability based on the assumption that all attributes are conditionally independent, given the class [40]. Classification results are based on 10-fold cross-validation.

2.3. Area Under the Receiver Operating Characteristics Curve (AUC) and Kappa

We selected the area under the receiver operating characteristics curve (AUC) and kappa as major evaluation criteria. The AUC value can be obtained by calculating the area under the receiver operating characteristics (ROC) curve, because an ROC curve is a two-dimensional graph [41]. AUC is widely used in medical sciences, signal detection, bioinformatics, medicine statistics, and biology to quantify the quality of a prediction or classification model, because it is a threshold-independent measure [41, 42]. AUC values of 1, 0.5, and 0 indicate a perfect diagnosis model, random diagnosis, and perfectly wrong diagnosis, respectively.

Cohen's kappa, introduced by Cohen, is considered a more accurate and robust evaluation criterion to measure the accuracy of binary and multi-classification, based on theoretical merits in statistics and medical sciences [40, 43]. The means of performance according to ranges of kappa values are as follows: 0 (poor); 0–0.2 (slight); 0.2–0.4 (fair); 0.4–0.6 (moderate); 0.6–0.8 (substantial, good); 0.8–1 (almost perfect, very good). Measures are defined as follows [44]:

$$Kappa = \frac{P_a - P_c}{1 - P_c},$$

where P_a is the overall agreement probability, and P_c is the probability that the agreement occurred by chance. For specific performance analysis, we determined precision, *F*-measure, accuracy, sensitivity, and 1-specificity.

3. Results and Discussion

3.1. Classification Results

For performance analysis of all experiments, the kappa and AUC of the 6 datasets (groups) are shown in Figure 2.

In AUC evaluation, the best classification performance among overall experiments was an AUC of 0.931 in the Male-61-over group. AUC values of the method with MDL discretization in all groups except for the Female-61-over group ranged from 0.760 to 0.931, while those of the method without MDL discretization ranged from 0.730 to 0.860. The classification performance of the second method with MDL discretization was better than that of the first method without MDL discretization, but in the Female-60-over group, the performance of the first method was higher than that of the second method.

In kappa evaluation, the performances of the method with MDL in Female-21-40, Female-41-60, Male-21-40, and Male-41-60 were higher than the performances of the method without MDL, while performances of the method without MDL in older groups were superior to those of the method with MDL. For instance, in Male-21-40, AUC and kappa values of the method with MDL showed improvements of 0.052 and 0.126, respectively, whereas in the Female-61-over group, AUC and kappa values of the method without MDL showed decreases of 0.208 and 0.195, respectively.

Although our results showed that the normal/overweight classification was more successful with MDL discretization than without, we cannot guarantee that the classification using MDL would always produce superior results. Specific results of the classification performance in the 6 groups are presented in Tables 2 and 3. Particularly, the classification of normal and overweight classes in the Female-61-over group is very difficult, compared to the other groups. This phenomenon is discussed in Section 3.4.

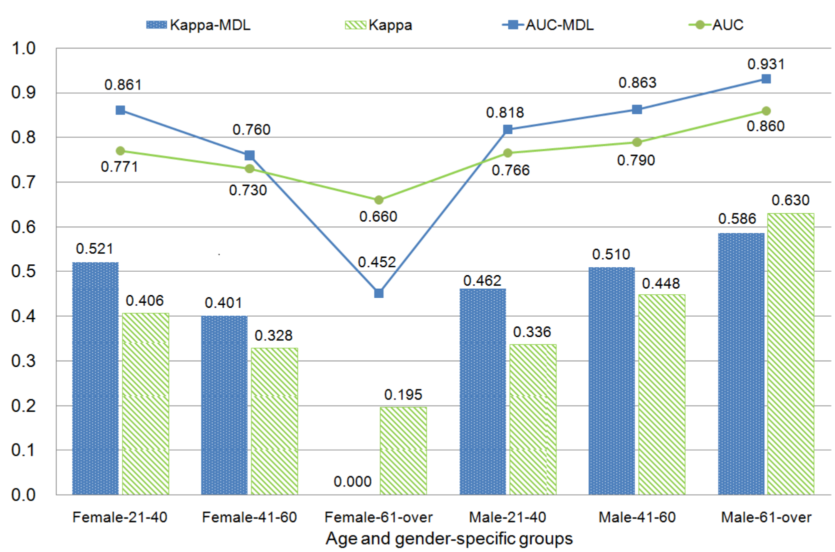

Figure 2. Performance Evaluations based on AUC and Kappa of the 6 Groups Derived with MDL Discretization (AUC-MDL and Kappa-MDL) and without MDL Discretization (AUC and Kappa)

Table 2. Specific Evaluation of Experimental Data using MDL Discretization

Group	Class	Sensitivity	1-specificity	Precision	*F*-Measure	Accuracy
Female-21-40	Normal	0.884	0.377	0.852	0.868	80.8%
	Overweight	0.623	0.116	0.686	0.653	
Female-41-60	Normal	0.653	0.253	0.685	0.668	70.4%
	Overweight	0.747	0.347	0.718	0.732	
Female-60-over	Normal	0	0	0	0	70.2%
	Overweight	1	1	0.702	0.825	
Male-21-40	Normal	0.704	0.233	0.644	0.673	74.3%
	Overweight	0.767	0.296	0.812	0.789	
Male-41-60	Normal	0.747	0.224	0.663	0.702	76.5%
	Overweight	0.776	0.253	0.839	0.806	
Male-61-over	Normal	0.958	0.278	0.605	0.742	79.5%
	Overweight	0.722	0.042	0.975	0.83	

Table 3. Specific Evaluation of Experimental Data without MDL Discretization

Group	Class	Sensitivity	1-specificity	Precision	*F*-Measure	Accuracy
Female-21-40	Normal	0.788	0.364	0.842	0.814	74.4%
	Overweight	0.636	0.212	0.551	0.59	
Female-41-60	Normal	0.684	0.354	0.62	0.65	66.4%
	Overweight	0.646	0.316	0.708	0.676	
Female-60-over	Normal	0.472	0.271	0.425	0.447	65.3%
	Overweight	0.729	0.528	0.765	0.747	
Male-21-40	Normal	0.685	0.333	0.552	0.612	67.4%
	Overweight	0.667	0.315	0.779	0.719	
Male-41-60	Normal	0.734	0.269	0.617	0.671	73.2%
	Overweight	0.731	0.266	0.824	0.775	
Male-61-over	Normal	0.833	0.167	0.69	0.755	83.3%
	Overweight	0.833	0.167	0.918	0.874	

3.2. Statistical Analysis of BMI and Facial Characteristics

Results from the statistical analysis of the 6 groups according to age and gender are presented in Tables 4-9. We considered only features with p-values less than 0.05; therefore, features shown for each age- and gender-group are different. The statistical analysis data are expressed as mean (standard deviation [Std]).

The differences between the normal and overweight classes were analyzed with the independent two-sample t-test using the SPSS data analysis program for Windows (version 19, SPSS Inc., Chicago, IL, USA).

A total of 42 features exhibited statistically significant differences between the normal and overweight classes ($p < 0.05$), and 11 of these features exhibited highly significant differences ($p < 0.0000$) in the Female-21-40 group. In the Female-41-60 group, differences in 8 of 21 features with p-values less than 0.05 were highly significant ($p < 0.0000$). Detailed analysis of the Female-21-40 and Female-41-60 groups was presented in our previous study [35].

None of the features in Female-61-over had a p-value <0.0000, and only 2 features in this group had p-values less than 0.005: EUL_L_*el*5 ($t = 3.157$, $p = 0.0020$) and FA18_17_43 ($t = 0.0043$, $p = 0.0043$). Thus, the classification performance of the Female-61-over group was poor compared to those of the other groups. In Male-21-40, differences in 7 of 19 features with p-values less than 0.05 were highly significant ($p < 0.0000$). In Male-41-60, differences in 6 of 36 features with p-values less than 0.05 were highly significant. Further, in Male-61-over, differences in 4 of 20 features were highly significant.

Several features were observed only in particular groups. The features EUL_R_St, FD117_126, EUL_R_RMAX, Fh_Cur_Max_Distan, EUL_L_*el*2, EUL_R_*er*7, FDH12_14, EUL_L_*el*3, EUL_R_DH, and EUL_R_Khmean were found only in the Female-21-40 group. The feature FDH14_21 was found in Female-41-60, and FDH18_118 and FDH6_7 were found in the Female-61-over group. Only FA17_25_43 was found in Male-21-40, and SA12_09, Fh_Angle_73_72, FA17_25, FDV9_12, EUL_L_Sb, and EUL_R_*er*5 were found in the Male-41-60 group. FDV52_50, FDV52_81, FD12_21, and FDV81_50, in particular, were found in the Male-60-over group.

Many features with a broad range of applicability and significant differences between the normal and overweight status were found in the age- and gender-specific groups. FD43_143 and FD94_194 were significantly different in all the 6 groups. This is not surprising because if the distances between points 43 to 143 and between points 94 to 194 in certain frontal images are wide, the individual is generally considered overweight. The features FA118_117_143, FA18_17_43, FD43_143, FD94_194, FR02_psu, FR05_psu, and FR08_psu were commonly found only in 3 female groups, and the features FArea02, FArea03, FD43_143, FD53_153, FD94_194, FDH25_125, FDH33_133, and FDV14_21 were found only in 3 male groups. FA118_117_143 and FA18_17_43 were significantly different in all groups, except Male-61-over. FA18_17_43 represents the angle of points 18, 17, and 43 in a frontal image. We think that these features are useful for discriminating normal from overweight. In previous studies, Levine et al. [21] argued that the quantity of buccal (cheek) fat is strongly related to visceral abdominal fat. Similarly, the results from the current study showed that the difference in the feature FAarea_03 (cheek area) was highly significant between normal and overweight in Female-21-40 ($t = -5.637$ and $p < 0.0000$), Female-41-60 ($t = -4.245$ and $p < 0.0000$), Male-21-40 ($t = -3.293$ and $p < 0.0013$), Male-41-60 ($t = -4.207$ and $p < 0.0000$), and Male-61-over ($t = -3.602$ and $p < 0.0006$), indicating that cheek area or cheek fat is strongly associated with normal and overweight statuses.

In addition, there were common features that were significantly different between the same age groups of females and males. Fifteen features, FA118_117_143, FA118_125_143, FA17_18, FA18_17_43, FA18_25_43, FArea02, FArea03, FD43_143, FD53_153, FD94_194, FDH25_125, FDH33_133, FR05_psu, FR06_psu, and

FR08_psu, were common to females and males aged 21–40 years. Further, 16 features, including FA118_117_143, FA18_17_43, FArea02, FArea03, FD17_25, FD18_25, FD43_143, FD53_153, FD94_194, FDH25_125, FDH33_133, FDV12_14, FR02_psu, FR05_psu, FR06_psu, and FR08_psu, were common between females and males aged 41–60 years. In females and males aged 61–over, only FD43_143, FD94_194, and FR02_psu were common.

Table 4. Statistical Analysis of Female-21-40 using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df, degree of freedom)*

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FD17_26	Normal	189	9.473	1.317	264.0	3.118	0.0020
		Overweight	77	8.941	1.115	165.4		
2	FD117_126	Normal	189	9.483	1.303	264.0	3.319	0.0010
		Overweight	77	8.904	1.257	145.8		
3	FDH25_125	Normal	189	96.53	5.116	264.0	-2.690	0.0076
		Overweight	77	98.52	6.320	118.6		
4	FDH36_136	Normal	189	23.57	2.469	264.0	-2.750	0.0064
		Overweight	77	24.46	2.191	157.9		
5	FD18_25	Normal	189	29.94	2.675	264.0	-2.036	0.0428
		Overweight	77	30.68	2.753	137.5		
6	FD43_143	Normal	189	125.2	7.101	264.0	-8.625	0.0000
		Overweight	77	133.6	7.384	136.2		
7	FD53_153	Normal	189	145.4	5.941	264.0	-5.991	0.0000
		Overweight	77	150.7	7.642	115.2		
8	FD94_194	Normal	189	140.1	6.022	264.0	-8.875	0.0000
		Overweight	77	147.6	6.934	125.1		
9	FDH33_133	Normal	189	147.2	5.630	264.0	-7.261	0.0000
		Overweight	77	153.1	7.020	117.8		
10	FA18_17_25	Normal	189	126.2	6.591	264.0	-2.684	0.0077
		Overweight	77	128.6	6.750	138.1		
11	FA118_117_125	Normal	189	125.0	7.339	264.0	-3.560	0.0004
		Overweight	77	128.3	6.199	165.7		
12	FA18_25_43	Normal	189	95.38	5.104	264.0	-3.722	0.0002
		Overweight	77	97.91	4.896	146.6		
13	FA118_125_143	Normal	189	96.16	4.753	264.0	-3.396	0.0008
		Overweight	77	98.39	5.082	133.0		
14	FA18_17_43	Normal	189	76.97	6.255	264.0	-4.390	0.0000
		Overweight	77	80.66	6.108	144.2		
15	FA118_117_143	Normal	189	76.82	6.824	264.0	-4.644	0.0000
		Overweight	77	80.90	5.583	171.1		
16	FA117_125	Normal	189	21.24	3.645	264.0	3.983	0.0001
		Overweight	77	19.19	4.142	126.4		
17	FA17_18	Normal	189	34.01	5.091	264.0	2.002	0.0463
		Overweight	77	32.61	5.320	135.7		
18	FR02_psu	Normal	189	0.318	0.044	264.0	4.199	0.0000
		Overweight	77	0.293	0.041	148.4		
19	FR05_psu	Normal	189	1.178	0.055	264.0	4.183	0.0000
		Overweight	77	1.148	0.048	160.4		
20	FR06_psu	Normal	189	2.039	0.117	264.0	-5.334	0.0000
		Overweight	77	2.123	0.115	142.4		
21	FR08_psu	Normal	189	1.736	0.151	264.0	-5.783	0.0000
		Overweight	77	1.854	0.147	144.4		
22	FArea02	Normal	189	6470	644.4	264.0	-2.106	0.0362
		Overweight	77	6654	652.2	139.5		
23	FArea03	Normal	189	3596	364.9	264.0	-5.637	0.0000

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
		Overweight	77	3873	361.9	142.1		
24	Fh_Cur_Max_Distan	Normal	189	3.654	1.564	264.0	1.984	0.0483
		Overweight	77	3.233	1.585	139.4		
25	FDH12_14	Normal	189	18.58	2.713	264.0	-3.006	0.0029
		Overweight	77	19.69	2.817	136.4		
26	Nose_Angle_14_12	Normal	189	61.07	4.611	264.0	2.946	0.0035
		Overweight	77	59.29	4.108	157.3		
27	Nose_Angle_12_14_21	Normal	189	106.7	4.634	264.0	2.397	0.0172
		Overweight	77	105.1	5.237	127.0		
28	EUL_L_*el*2	Normal	189	-0.637	0.095	264.0	-3.135	0.0019
		Overweight	77	-0.597	0.087	152.4		
29	EUL_L_ *el*3	Normal	189	-0.220	0.118	264.0	-3.206	0.0015
		Overweight	77	-0.170	0.110	151.2		
30	EUL_L_ *el*6	Normal	189	0.483	0.105	264.0	3.473	0.0006
		Overweight	77	0.432	0.113	131.4		
31	EUL_L_DH	Normal	189	3.178	0.248	264.0	-2.530	0.0120
		Overweight	77	3.268	0.292	123.0		
32	EUL_L_Sf	Normal	189	0.408	0.106	264.0	2.442	0.0153
		Overweight	77	0.371	0.132	117.8		
33	EUL_R_*er*2	Normal	189	-0.630	0.087	264.0	-3.957	0.0001
		Overweight	77	-0.582	0.095	129.8		
34	EUL_R_ *er*3	Normal	189	-0.208	0.112	264.0	-2.822	0.0051
		Overweight	77	-0.167	0.100	156.4		
35	EUL_R_ *er*6	Normal	189	0.466	0.106	264.0	2.492	0.0133
		Overweight	77	0.430	0.111	134.8		
36	EUL_R_ *er*7	Normal	189	0.647	0.235	264.0	2.432	0.0165
		Overweight	77	0.556	0.290	118.6		
37	EUL_R_DH	Normal	189	3.188	0.226	264.0	-4.292	0.0000
		Overweight	77	3.322	0.241	133.3		
38	EUL_R_RMAX	Normal	189	0.443	0.069	264.0	2.061	0.0403
		Overweight	77	0.424	0.066	146.2		
39	EUL_R_St	Normal	189	-0.633	0.117	264.0	-2.525	0.0122
		Overweight	77	-0.592	0.123	135.1		
40	EUL_R_Sf	Normal	189	0.395	0.106	264.0	2.452	0.0149
		Overweight	77	0.360	0.104	143.7		
41	EUL_R_Khmean	Normal	189	0.024	0.007	264.0	2.868	0.0045
		Overweight	77	0.022	0.007	156.3		
42	PDH44_53	Normal	189	89.38	6.081	264.0	-3.017	0.0028
		Overweight	77	91.79	5.527	154.3		

* quoted from our previous paper [35].

Table 5. Statistical Analysis of Female-41-60 using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df, degree of freedom)*

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FDH25_125	Normal	193	94.63	5.466	420.0	-3.097	0.0021
		Overweight	229	96.29	5.493	408.6		
2	FDH36_136	Normal	193	24.84	2.283	420.0	-2.055	0.0405
		Overweight	229	25.36	2.805	419.5		
3	FD18_25	Normal	193	29.37	3.287	420.0	-2.199	0.0284
		Overweight	229	30.04	2.923	388.0		
4	FD17_25	Normal	193	17.83	2.717	420.0	-2.076	0.0385
		Overweight	229	18.36	2.471	392.4		
5	FD43_143	Normal	193	127.4	6.471	420.0	-8.184	0.0000

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
		Overweight	229	133.1	7.721	420.0		
6	FD53_153	Normal	193	143.9	6.343	420.0	-4.848	0.0000
		Overweight	229	147.2	7.141	418.8		
7	FD94_194	Normal	193	141.8	6.010	420.0	-8.385	0.0000
		Overweight	229	146.9	6.485	416.2		
8	FDH33_133	Normal	193	146.8	6.057	420.0	-6.615	0.0000
		Overweight	229	150.9	6.582	416.7		
9	FA18_25_43	Normal	193	99.88	5.308	420.0	-2.589	0.0100
		Overweight	229	101.2	4.954	397.1		
10	FA118_125_143	Normal	193	99.74	4.776	420.0	-4.343	0.0000
		Overweight	229	101.9	5.373	418.8		
11	FA117_125_143	Normal	193	124.7	5.380	420.0	-2.438	0.0152
		Overweight	229	126.0	5.471	410.2		
12	FA18_17_43	Normal	193	81.11	6.753	420.0	-2.676	0.0077
		Overweight	229	82.85	6.574	404.1		
13	FA118_117_143	Normal	193	80.69	6.449	420.0	-3.632	0.0003
		Overweight	229	83.16	7.350	419.3		
14	FR02_psu	Normal	193	0.295	0.044	420.0	2.182	0.0297
		Overweight	229	0.285	0.051	419.6		
15	FR05_psu	Normal	193	1.154	0.046	420.0	3.966	0.0001
		Overweight	229	1.135	0.049	414.8		
16	FR06_psu	Normal	193	2.006	0.104	420.0	-5.688	0.0000
		Overweight	229	2.068	0.121	419.7		
17	FR08_psu	Normal	193	1.743	0.134	420.0	-5.935	0.0000
		Overweight	229	1.827	0.157	419.9		
18	FArea02	Normal	193	6358	618.3	420.0	-2.212	0.0275
		Overweight	229	6501	696.7	418.9		
19	FArea03	Normal	193	3886	397.6	420.0	-4.245	0.0000
		Overweight	229	4052	402.6	409.6		
20	FDV12_14	Normal	193	33.85	3.313	420.0	2.516	0.0123
		Overweight	229	33.00	3.571	416.1		
21	FDH14_21	Normal	193	12.90	1.633	420.0	2.163	0.0311
		Overweight	229	12.53	1.889	419.7		
22	Nose_Angle_14_21	Normal	193	45.73	4.983	420.0	-2.402	0.0168
		Overweight	229	46.98	5.765	419.7		

* quoted from our previous paper [35].

Table 6. Statistical Analysis of Female-61-over using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df, degree of freedom)

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FDH18_118	Normal	36	36.76	4.471	119.0	2.125	0.0357
		Overweight	85	34.97	4.129	61.50		
2	FD43_143	Normal	36	126.4	8.192	119.0	-2.729	0.0073
		Overweight	85	130.7	8.000	64.59		
3	FD94_194	Normal	36	141.4	6.726	119.0	-2.134	0.0349
		Overweight	85	144.6	7.720	75.20		
4	FA118_117_125	Normal	36	128.1	7.290	119.0	-2.080	0.0396
		Overweight	85	131.6	8.714	78.24		
5	FA18_17_43	Normal	36	83.72	6.560	119.0	-2.910	0.0043
		Overweight	85	87.40	6.282	63.48		
6	FA118_117_143	Normal	36	84.87	6.953	119.0	-2.127	0.0355
		Overweight	85	88.00	7.568	71.44		
7	FA17_18	Normal	36	27.99	6.148	119.0	2.094	0.0384

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
		Overweight	85	25.74	5.064	56.08		
8	FR02_psu	Normal	36	0.259	0.045	119.0	1.984	0.0496
		Overweight	85	0.240	0.050	72.97		
9	FR05_psu	Normal	36	1.156	0.049	119.0	2.503	0.0137
		Overweight	85	1.133	0.046	61.77		
10	FR08_psu	Normal	36	1.734	0.171	119.0	-2.079	0.0398
		Overweight	85	1.800	0.154	60.22		
11	FDH6_7	Normal	36	14.91	4.836	119.0	2.197	0.0299
		Overweight	85	12.69	5.173	70.26		
12	EUL_L_*el*5	Normal	36	0.482	0.119	119.0	3.157	0.0020
		Overweight	85	0.407	0.120	66.59		

Table 7. Statistical Analysis of Male-21-40 using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df, degree of freedom)

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FDH25_125	Normal	54	99.65	5.953	142.0	-2.034	0.0438
		Overweight	90	101.7	5.633	106.9		
2	FD43_143	Normal	54	131.6	8.371	142.0	-6.387	0.0000
		Overweight	90	141.6	9.545	123.3		
3	FD53_153	Normal	54	150.5	6.530	142.0	-4.124	0.0001
		Overweight	90	155.8	7.972	128.8		
4	FD94_194	Normal	54	146.6	7.109	142.0	-6.531	0.0000
		Overweight	90	155.4	8.146	123.7		
5	FDH33_133	Normal	54	153.3	6.359	142.0	-4.972	0.0000
		Overweight	90	159.5	7.731	128.5		
6	FA18_25_43	Normal	54	96.16	6.435	142.0	-4.278	0.0000
		Overweight	90	100.8	6.148	107.7		
7	FA118_125_143	Normal	54	96.68	5.093	142.0	-4.444	0.0000
		Overweight	90	100.8	5.641	120.8		
8	FA17_25_43	Normal	54	117.4	7.449	142.0	-2.586	0.0107
		Overweight	90	120.3	6.181	96.1		
9	FA117_125_143	Normal	54	118.5	5.270	142.0	-2.612	0.0100
		Overweight	90	121.1	6.056	123.9		
10	FA18_17_43	Normal	54	82.37	6.350	142.0	-4.123	0.0001
		Overweight	90	87.32	7.912	130.4		
11	FA118_117_143	Normal	54	82.31	5.621	142.0	-4.244	0.0000
		Overweight	90	86.82	6.469	124.1		
12	FA17_18	Normal	54	29.35	4.013	142.0	2.643	0.0092
		Overweight	90	27.28	5.298	134.3		
13	FR05_psu	Normal	54	1.168	0.057	142.0	4.141	0.0001
		Overweight	90	1.129	0.053	105.2		
14	FR06_psu	Normal	54	2.024	0.124	142.0	-3.907	0.0001
		Overweight	90	2.113	0.138	121.3		
15	FR08_psu	Normal	54	1.740	0.170	142.0	-4.473	0.0000
		Overweight	90	1.879	0.187	119.9		
16	FArea02	Normal	54	6982	662.636	142.0	-2.176	0.0312
		Overweight	90	7255	766.437	124.5		
17	FArea03	Normal	54	4023	561.8	142.0	-3.293	0.0013
		Overweight	90	4313	480.9	98.5		
18	FDV14_21	Normal	54	13.37	2.025	142.0	-2.377	0.0188
		Overweight	90	14.16	1.867	104.6		
19	Nose_Angle_14_21	Normal	54	43.99	6.874	142.0	-2.269	0.0248
		Overweight	90	46.42	5.810	97.5		

Table 8. Statistical Analysis of Male-41-60 using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df: degree of freedom)

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FD17_26	Normal	79	8.134	1.451	211.0	2.376	0.0184
		Overweight	134	7.666	1.351	154.4		
2	FDH25_125	Normal	79	98.25	6.482	211.0	-3.185	0.0017
		Overweight	134	101.1	6.312	160.2		
3	FD18_25	Normal	79	30.86	3.650	211.0	-3.649	0.0003
		Overweight	134	32.56	3.057	141.6		
4	FD17_25	Normal	79	17.96	3.156	211.0	-2.729	0.0069
		Overweight	134	19.02	2.478	134.6		
5	FD43_143	Normal	79	134.5	8.123	211.0	-6.964	0.0000
		Overweight	134	143.2	9.144	179.4		
6	FD53_153	Normal	79	149.0	7.430	211.0	-5.461	0.0000
		Overweight	134	155.6	9.174	190.8		
7	FD94_194	Normal	79	148.6	6.720	211.0	-7.578	0.0000
		Overweight	134	156.8	8.199	189.4		
8	FDH33_133	Normal	79	153.0	6.685	211.0	-6.325	0.0000
		Overweight	134	160.0	8.460	193.6		
9	FA18_17_25	Normal	79	132.7	7.718	211.0	-3.350	0.0010
		Overweight	134	136.5	8.022	168.8		
10	FA118_117_125	Normal	79	132.1	7.077	211.0	-2.234	0.0265
		Overweight	134	134.5	7.945	179.0		
11	FA18_17_43	Normal	79	86.16	7.782	211.0	-3.400	0.0008
		Overweight	134	89.54	6.528	141.8		
12	FA118_117_143	Normal	79	86.35	7.379	211.0	-2.799	0.0056
		Overweight	134	89.01	6.248	142.9		
13	FA17_25	Normal	79	21.29	4.353	211.0	3.600	0.0004
		Overweight	134	18.92	4.793	176.5		
14	FA117_125	Normal	79	22.36	3.972	211.0	3.517	0.0005
		Overweight	134	20.26	4.351	175.8		
15	FR02_psu	Normal	79	0.266	0.052	211.0	4.290	0.0000
		Overweight	134	0.237	0.045	146.8		
16	FR05_psu	Normal	79	1.139	0.057	211.0	2.811	0.0054
		Overweight	134	1.119	0.047	141.5		
17	FR06_psu	Normal	79	2.007	0.134	211.0	-3.725	0.0003
		Overweight	134	2.080	0.142	171.5		
18	FR08_psu	Normal	79	1.768	0.180	211.0	-3.903	0.0001
		Overweight	134	1.864	0.168	154.7		
19	FArea02	Normal	79	6934	795.9	211.0	-3.082	0.0023
		Overweight	134	7287	817.2	167.2		
20	FArea03	Normal	79	4226	517.3	211.0	-4.207	0.0000
		Overweight	134	4560	585.0	180.0		
21	FDV9_12	Normal	79	28.66	4.056	211.0	-4.023	0.0001
		Overweight	134	31.06	4.303	171.5		
22	FDV12_14	Normal	79	36.77	3.961	211.0	2.841	0.0049
		Overweight	134	35.21	3.797	158.2		
23	FDV14_21	Normal	79	13.96	2.177	211.0	-2.413	0.0167
		Overweight	134	14.71	2.196	164.9		
24	Fh_Angle_73_72	Normal	79	69.79	7.566	211.0	2.134	0.0340
		Overweight	134	67.60	7.070	154.9		
25	Nose_Angle_14_12	Normal	79	58.38	4.560	211.0	2.086	0.0382
		Overweight	134	57.03	4.581	164.3		
26	SA12_09	Normal	79	86.03	6.427	211.0	-2.375	0.0185
		Overweight	134	88.12	6.034	155.5		
27	EUL_L_ *el*5	Normal	79	0.368	0.117	211.0	3.287	0.0012

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
		Overweight	134	0.314	0.114	160.1		
28	EUL_L_ *el*6	Normal	79	0.457	0.112	211.0	3.109	0.0021
		Overweight	134	0.406	0.118	171.0		
29	EUL_L_Sb	Normal	79	0.015	0.071	211.0	2.417	0.0165
		Overweight	134	-0.008	0.067	157.2		
30	EUL_L_Sf	Normal	79	0.382	0.095	211.0	3.211	0.0015
		Overweight	134	0.339	0.095	163.9		
31	EUL_R_*er*2	Normal	79	-0.530	0.109	211.0	-2.167	0.0313
		Overweight	134	-0.496	0.112	167.7		
32	EUL_R_ *er*3	Normal	79	-0.135	0.154	211.0	-2.078	0.0396
		Overweight	134	-0.093	0.122	135.0		
33	EUL_R_ *er*5	Normal	79	0.353	0.114	211.0	2.860	0.0047
		Overweight	134	0.308	0.109	157.1		
34	EUL_R_ *er*6	Normal	79	0.464	0.117	211.0	3.805	0.0002
		Overweight	134	0.399	0.122	169.7		
35	EUL_R_Sf	Normal	79	0.387	0.093	211.0	3.901	0.0001
		Overweight	134	0.333	0.099	172.1		
36	PDH44_53	Normal	79	93.24	7.317	211.0	-2.371	0.0186
		Overweight	134	95.76	7.610	168.9		

Table 9. Statistical Analysis of Male-61-over using Independent Two-sample t-test (N, number of subjects; Std, standard deviation; Df, degree of freedom)

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
1	FDH25_125	Normal	24	93.94	5.514	76.00	-4.558	0.0000
		Overweight	54	100.7	6.216	49.47		
2	FDH36_136	Normal	24	26.10	4.186	76.00	-2.348	0.0259
		Overweight	54	28.22	2.196	28.78		
3	FDV52_50	Normal	24	73.99	4.655	76.00	-2.973	0.0040
		Overweight	54	78.16	6.124	57.28		
4	FDV52_81	Normal	24	44.56	4.354	76.00	-2.307	0.0238
		Overweight	54	46.94	4.124	42.10		
5	FDV81_50	Normal	24	29.42	3.044	76.00	-2.050	0.0438
		Overweight	54	31.22	3.780	54.28		
6	FD18_25	Normal	24	29.10	3.377	76.00	-3.236	0.0018
		Overweight	54	32.21	4.127	53.45		
7	FD17_25	Normal	24	17.03	2.749	76.00	-2.699	0.0086
		Overweight	54	19.06	3.194	50.92		
8	FD43_143	Normal	24	132.5	9.063	76.00	-4.096	0.0001
		Overweight	54	141.1	8.288	40.83		
9	FD53_153	Normal	24	145.2	5.201	76.00	-4.375	0.0000
		Overweight	54	152.0	6.756	56.62		
10	FD94_194	Normal	24	144.8	7.094	76.00	-5.595	0.0000
		Overweight	54	154.3	6.883	43.01		
11	FDH33_133	Normal	24	148.6	5.250	76.00	-5.532	0.0000
		Overweight	54	157.2	6.757	56.13		
12	FR02_psu	Normal	24	0.250	0.044	76.00	2.369	0.0204
		Overweight	54	0.223	0.046	46.29		
13	FArea02	Normal	24	6385	697.9	76.00	-3.870	0.0002
		Overweight	54	7115	797.1	50.09		
14	FArea03	Normal	24	4117	516.4	76.00	-3.602	0.0006
		Overweight	54	4658	649.2	54.90		
15	FDV14_21	Normal	24	14.30	1.478	76.00	-2.401	0.0188
		Overweight	54	15.46	2.135	62.21		
16	FD12_21	Normal	24	50.70	3.118	76.00	-2.574	0.0120

Num.	Feature	Class	N	Mean	Std.	Df.	t	p-value
		Overweight	54	53.16	4.176	58.23		
17	Nose_Angle_12_14_21	Normal	24	104.1	5.496	76.00	-2.315	0.0233
		Overweight	54	106.9	4.664	38.37		
18	EUL_L_*el*6	Normal	24	0.431	0.164	76.00	2.480	0.0153
		Overweight	54	0.335	0.155	42.07		
19	EUL_L_DH	Normal	24	3.378	0.316	76.00	-3.216	0.0019
		Overweight	54	3.615	0.292	41.19		
20	EUL_L_Sf	Normal	24	0.366	0.108	76.00	2.605	0.0110
		Overweight	54	0.301	0.100	41.26		

3.3. Limitations

In the classification of BMI using facial features, classification performances were reasonable in 5 groups but poor in the Female-61-over group, such that features extracted from the faces of females aged ≥61 years did not reflect the females' BMI. Menopause may be one of the reasons for the issues with BMI classification in females aged ≥61 years. This hypothesis is supported by menopause and body composition studies [45-51]. Using Student t-test and univariate regression analysis, Douchi et al. [45] showed that body composition is statistically different between pre- and postmenopausal females, and trunk lean mass, in particular, exhibits a greater decrease after menopause than the lean mass in other parts of the body. Skrzypczak et al. [46, 47] showed that postmenopausal females have higher WHR, W/Ht, and BMI than premenopausal females because of hormonal changes, and showed that the difference in BMI between the 2 groups was statistically significant. Guo et al. [48] and Dobs et al. [49] argued that postmenopausal females have significantly higher total body fat, body weight, and BMI than premenopausal females. Because menopause leads to changes in fatty tissue distribution, we believe that BMI diagnosis using facial features in older female groups is difficult. Future studies will focus on establishing the cause of this problem.

As mentioned in Section 2.2, the diagnosis of normal, overweight, and obese using BMI values differs according to region, race, and national economic status. This is a problem with the BMI classification criteria of WHO. For example, morphological characteristics of the face differ according to race. Using anthropometric face analysis, Porter and Olson [52] showed that facial characteristics, such as nose length, nasal width, facial width, forehead height, and eye-fissure width, are significantly different between African-American and Caucasian females. This is one of the factors that hamper the successful classification of a broad range of patients or individuals. Thus, an ideal classification method should reflect the morphological characteristics of the face according to ethnic group, region, economic status, and BMI criteria.

4. Summary

Facial features of patients or potential patients offer clues to present and future health complications, particularly obesity-associated diseases, such as CVD, type 2 diabetes, and breathlessness. In this study, we examined the relationship between facial characteristics and BMI and proposed a method for the classification of normal and overweight based on facial features in age- and gender-specific groups. Our results may promote fast, cost-efficient, and automatic diagnosis of obesity in remote healthcare, and facilitate real-time monitoring of patients with chronic diseases associated with BMI.

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Appendix Table. Features and brief descriptions quoted from our previous paper [35]

Feature	Description
FD n_1_ n_2	Distance between point n_1 and n_2 in frontal and profile photographs
FDH n_1_ n_2	Horizontal distance between n_1 and n_2 in frontal and profile photographs
FDV n_1_ n_2	Vertical distance between n_1 and n_2 in frontal and profile photographs
FA n_1_ n_2_ n_3	Angle of three points n_1, n_2, and n_3 in frontal and profile photographs
FA n_1_ n_2	Angle between the line through 2 points n_1 and n_2 and a horizontal line in frontal and profile photographs
FR02_psu	FD(17,26)/FD(18,25)
FR03_psu	(FD[18,25] + FD[118,125])/FDH(33,133)
FR05_psu	FDH(33,133)/FD(43,143)
FR06_psu	FDH(33,133)/FDV(52,50)
FR08_psu	FD(43,143)/FDV(52,50)
FArea02	Area of the contour formed by the points 53,153, 133, 194, 94, 33, and 53 in a frontal photograph
FArea03	Area of the contour formed by the points 94, 194, 143, 43, and 94 in a frontal photograph
Fh_Cur_Max_Distan	Distance between points 7 and 77 in a profile photograph
Fh_Angle_ n_1_ n_2	Angle between the line through 2 points n_1 and n_2 and a horizontal line in frontal and profile photographs
Nose_Angle_ n_1_ n_2	Angle between the line through 2 points n_1 and n_2 and a horizontal line in frontal and profile photographs
Nose_Angle_ n_1_ n_2 _n_3	Angle of 3 points n_1, n_2, and n_3 in frontal and profile photographs
SA n_1_ n_2	Angle between the line through 2 points n_1 and n_2 and a horizontal line in frontal and profile photographs
Fh_Cur_Max_R79_69	FD(77,9)/FD(6,9)
Nose_Area_ n_1_ n_2_ n_3	Area of the triangle formed by 3 points n_1, n_2, and n_3 in a profile photograph
EUL_L_*el*1 ~ EUL_L_*el*7	Slope of the tangent at a point (*el*1~*el*7) in a frontal photograph

Feature	**Description**
EUL_L_DH	FDH($el1$, $el7$)
EUL_L_MAX	FDH($el1$, el_{max})
EUL_L_RMAX	FDH($el1$, el_{max})/FDH($el1$, $el7$)
EUL_L_Sb	FDV($el7$, $el1$)/FDH($el7$, $el1$)
EUL_L_St	FDV(el_{max}, $el7$)/FDH(el_{max}, $el7$)
EUL_L_Sf	FDV(el_{max}, $el1$)/FDH(el_{max}, $el1$)
EUL_L_Khmean	Average curvature of the left (or right) upper eyelid contour in a frontal photograph
EUL_L_khmax	Maximum curvature of the left (or right) upper eyelid contour in a frontal photograph
EUL_R_$er1$~ EUL_R_$er7$	Slope of the tangent at a point ($er1$~ $er7$) in a frontal photograph
EUL_R_DH	FDH($er1$,$er7$)
EUL_R_MAX	FDH($er1$,er_{max})
EUL_R_RMAX	FDH($er1$,er_{max})/FDH($er1$,$er7$)
EUL_R_Sb	FDV($er7$,$er1$)/FDH($er7$,$er1$)
EUL_R_St	FDV(er_{max},$er7$)/FDH(er_{max},$er7$)
EUL_R_Sf	FDV(er_{max},$er1$)/FDH(er_{max},$er1$)
EUL_R_Khmean	Average curvature of the left (or right) upper eyelid contour in a frontal photograph
EUL_R_khmax	Maximum curvature of the left (or right) upper eyelid contour in a frontal photograph
PDH44_53	Horizontal distance between n_1 and n_2 in frontal and profile photographs