Journal of Information Systems and Informatics
Vol. 5, No. 1, March 2023 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v5i1.451 Published By DRPM-UBD

Software Approach to BMI and Obesity Determination using Facial Extraction Techniques

Bukohwo Michael Esiefarienrhe[1], Itumeleng Michael Maine[2]

[1,2] MaSIM and Computer Science Department, North-West University, South Africa
Email: [1]michael.esiefarienrhe@nwu.ac.za, [2]mainemitu@gmail.com

Abstract

The focus on COVID-19 pandemic has led doctors to reduce consultation and restrict hospital visitations by patients, a decision that has resulted in the increased cases of obesity coupled with restrictions on movement and exercises. Obesity places the health of people in danger, since it is associated with poor mental health, reduce quality of life, increases the risk of diabetes, heart disease, stroke and introduces certain types of cancer. The aim of this study therefore is to design and develop a face-to-BMI mobile application that enable people to learn about their Body Mass Index (BMI), get their obesity status, as well as receive doctor recommendations (or counsel) from the comfort of their homes using their mobile devices. The design science research methodology was used in the design and development of the mobile application for obesity assessment. A mobile phone is required to take the face photo of the users after which the algorithm will perform face detection, looking for all possible facial features such as the width to upper facial height ratio (WHR), cheek to jaw width (WJWR), perimeter of area ratio (PAR), lower face to face height ratio (FW/FH), mean of eyebrow height (MEH) using facial measurements such as the iris, mouth corners, eyebrows, and nostril. The algorithm then performs Active Shape Model (ASM) fitting. The mobile app was tested with five (5) participants and the results shown significant improvement in obesity detection and ease of use.

Keywords: ASM fitting, Obesity, Facial recognition, BMI, Mobile application for obesity

1 INTRODUCTION

Obesity has become a major crisis in the lives of several people as it may acts as a doorway for other diseases in the human body. Obesity is a type of abnormal body fat that poses a health concern to humans and raises the likelihood of developing health problems: gallbladder disease, heart disease, stroke etc and can lower the quality of life as it can associated to a high risk of mental illness [1, 2]. Between the year 2020 and now, emphasis has been on the COVID-19 pandemic consequently most individuals with obesity do not receive much attention and as such, cases of obesity have risen exponentially in both developed and developing countries [3, 4, 5]. According to a global research, 2.8 million people die each year because of

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

being overweight or obese, with overweight or obesity accounting for 35.8 million (2.3%) of global disability-adjusted life years [6]. Obesity is currently diagnosed in over 600 million people globally, with the number expected to rise to 1.12 billion by 2030 [6, 7]. Research revealed that obesity is induced by eating more calories than the body can utilise, as well as irregular sleeping patterns [8]. Premature death, cardiovascular illnesses, high blood pressure, and osteoarthritis are some of the conditions associated with obesity and overweight [8,9].

Most countries implemented lockdown to control the spread of the corona virus, which causes jobs lost leading to anxiety, stress, and a sanitary lifestyle. The rise in obesity incidence in several countries is now referred to as "obesity epidemic". Obese patients' doctor consultations were cancelled, and hospital visits were reduced because of the Corona pandemic with negative impact on the lifestyle of obese people. Most people are unable to visit doctors [10] to have their weight or body mass index (BMI) checked, and some are unaware of the signs of being underweight, overweight, or obese. Apart from lack of doctor's consultation within the pandemic era, most hospitals (mostly in developing countries) have limited, and some do not have adequate technology to measure the severity of obesity for their patients. Lack of physical activity, poor eating patterns, genetic factors, or a combination of all three variables are the most common causes of obesity [8,9].

Most hospitals, especially public hospitals, were overcrowded, which lead to most people being too lazy to visit their respective doctors or have an obesity consultation thus aggravating their obesity condition. Obesity is difficult and intensive since not everyone is aware of its dangers; thus, it is not taken seriously. It is also difficult to be treated since most medications have side effects, and it can be exacerbated by other disorders. The condition itself influences the immune system, which may promote or strengthen the above-mentioned diseases. Going to the hospital to see a doctor is the most common approach to find out if someone is obese. Most people may find this difficult, as people in rural areas must travel vast distances to hospitals. The use of body mass index (BMI), height, weight, and waist-to-hip ratio (WHR) through the gathering of anthropometric data of persons is a well-known assessment used to identify whether someone is underweight, overweight, obese, or extremely obese. Percentage body fat (PBF), body fat mass (BFM), and visceral fat area (VFA) are advanced body composition analysis-based measurements that are commonly used to quickly detect obesity [1] which are also not easily carried out without a visit to hospital or health facilities with the guidance of experts thus aggravating obesity challenges.

Thus, this paper is aimed at presenting a mobile software application that was developed to mitigate the effects of the COVID-19 lockdown on individuals by enabling them to determine their BMI status and assist them to undergo series of activities that could culminate to a healthy lifestyle from the comfort of their home

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

using their mobile devices. The rest of the paper is organised as follows. Section two discusses some literatures related to obesity software and models. Section three discusses the methodology used in the software development. Section four discusses the results of the software application and test data, and section five gives the conclusion and future direction of the research.

2. RELATED LITERATURE

BMI has recently been employed as a predictor and estimate of social behaviour in several societies. Most individuals with similar BMI readings are more likely to be connected as friends on social networks, according to studies and initiatives, than those with differing BMI values [11,12,13]. Thus, women with higher BMI who are classified as obese experience weight-based discrimination for example, in employment, modelling etc [12]. This raises the unemployment rate of obese people globally and thus puts them in a dangerous mental state [13], as this may lead them to believe that they are incapable of executing any activity than regular (less obese) human being. Thus, while this study [13] demonstrates the issues that fat people confront, it does not offer a solution on how they might be assisted, either through software intervention or by educating people on the danger of obesity.

The study by [3][14] is related to information on food trends and lifestyle changes during the Covid-19 lockdown outbreak. Their research's major motive was to look at the influence of corona virus epidemic due to food consumption, human health, including the changes in human lifestyle at home through social isolation and social distance. Their study also gave solution for preserving excellent health in the face of the pandemic. According to their research, the implementation of lockdown, physical separation, and self-isolation had a negative impact on every citizen by affecting their eating habits and everyday behaviour, making staying at home a restriction and limitation for many people, as no gym is allowed for exercises, causing digital education and smart working. In addition, boredom is produced by a disruption in work routine (quarantine), which leads to increased energy use [3]. Similarly, many individuals lost their jobs, and reading or hearing about the outbreak of covid-19 case expansion in the media may cause further stress [15], which may lead to a variety of mental illnesses, including obesity. They reported that stress causes overeating, with a higher likelihood of "comfort foods", or sugar-rich meal desires [3]. As a result, consuming too much sugar or carbohydrates enhances the severity of covid-19 and cardiovascular illnesses. Therefore, obese persons are more prone to be infected by the corona virus because they are exposed to greater levels of proinflammatory cytokines than normal-weight people [3][16]. Because of the limited availability of fresh food, particularly fish, vegetables, and fruit, most people choose quick meals, such as junk foods and snacks [3]. Most individuals grow fat because of eating such foods, and they still do not receive help since they are unable to visit their nearest

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

hospitals or consult their doctors [3]. According to health research, too much sleep contributes to weight growth, thus nutrition has a very important effect on the standard of sleep [3][10]. They utilized a web-survey to analyse changes in eating behaviour, statistical analysis (MD adherence) and provided recommendations on suitable meals and eating pattern but they failed to create mobile application to assist in obesity identification and control.

Similarly, "Health Impacts of Obesity" is one of the studies that shows a link between obesity/overweight and its effects on many aspects of people's health [17] as the authors identified metabolic disease based on the risk factor linked with obesity, which eventually leads to significant health effects for many people and a burden on health care in general. Obese individuals suffer from severe joint aches, a variety of diseases, as well as psychological and social damage [17]. Cancers (ovarian, prostate, kidney, breast, pancreatic, sophageal, colorectal, endometrial), hypertension, pulmonary embolism, chronic back pain, congestive heart failure, stroke, coronary artery disease, osteoarthritis, and asthma, as well as an increased risk of disability, are among the obesity associativity co-morbidities they mentioned in their research [17]. As a result, countless people have died across the world. They utilize BMI as the best predictor of overall mortality instead of other anthropometric measures (such as waist circumference, waist-to-hip ratio) for the prediction of obesity, which is like our findings [17][6]. They claimed that fat persons face psychological stigmatization and impairments in a variety of contexts, including educational procedures, health-care delivery, and job arrangements [17]. They also face humiliation, social bias, and ridicule [17]. From a spiritual standpoint, they [17] claim that emotional eating has a significant impact on nutritional behaviours such as binge eating, caloric intake, and bulimic eating urges. The most effective way to have a better spiritual perspective is to educate everyone about the obesity epidemic. They clearly described and provided additional details about the causes of obesity. However, their drawback is that not everyone will be able to access their paper and learn more about obesity because in our research we developed a mobile app for educating obese people because mobile devices have becomes widely used.

"Context aware mobile agent for decreasing stress and obesity by stimulating physical activity" by [11] describes or focuses mostly on encouraging physical activities to reduce both stress and obesity. According to the researchers, there is a link between stress and obesity, which is best addressed by physical activity. They created a context-aware android smartphone app that uses contextual data to provide users with alarm messages and motivate them to exercise [11]. Their program senses the user's desired physical environment using open-source web APIs as well as the smartphone's built-in sensors. The application detects the user's location and weather, temperature, humility level, and forecast, as well as generate a pattern that is sent to the web server so that the user can receive the notification [11]. The response of the user to the notification is also recorded. They used the

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

'Open Weather API' to determine weather information in their app. However, the application requires an internet connection to communicate the created pattern and user's ID to the web server via the browser, which may be a difficult condition for individuals who do not have access to the internet particularly from developing and poor countries.

Similarly, an application was designed to follow the user's lifestyle in the study "Cloud and Sensors Based Obesity Monitoring System" [8]. They combine data analytics, cloud computing, and sensors like force-sensing resistors to track user lifestyles (FSR). The device uses the user's BMI to set a smart alarm, encourage them to exercise, and recommend a healthy diet [8]. A cloud-based Internet of Things (IoT) platform connects cloud services, a weighing box, and a user application, all of which are connected through a cloud-based Internet of Things (IoT) platform. To view their BMI and set an alarm, users must first register and connect with their smartphone [8]. If the user's alarm goes off, the only way to silence it is to step on the weighing box, which has an FSR sensor that senses applied force or pressure and calculates the user's weight based on those numbers. The BMI is then calculated by the hardware inside the box, which subsequently sends a notification to the user's smartphone and cloud services via IoT platforms. Their technology consists of microcontrollers that connect to an IoT platform through Bluetooth and compute and save data using an algorithm. The primary flaw in their system is that not everyone can afford to buy all the necessary equipment to complete all these chores to calculate their BMI and determine their obese status.

Furthermore, this study, titled "A computational approach to body mass index prediction using face pictures," explains how the human face is encoded with a wealth of important information, including personality traits, beauty, emotional expression, ethnicity, identification, age, and gender. Furthermore, several studies in the fields of computer science, psychology, and human perspective have shown that there is a significant link between body mass index (BMI) and human weight, prompting this study [18] to examine and uncover such relationships. They employed about 14, 500 face picture datasets, with BMI prediction from facial characteristics of those photos being formulated as a machine version issue [18]. They suggested that predicting BMI from a photo might be highly beneficial in assessing body beauty, including health. Face detection, face normalizing, ASM fitting, geometry/ratio features, features normalization, and regression are the six procedures or phases they go through to determine their BMI from face picture. They utilized Active Shape Model (ASM) for determining the amount of fiducially points in each image because of its exceptional performance in extracting face characteristics and finding structures in medical imaging for a variety of applications [18]. With the aid of their psychology research, their program was able to identify and evaluate all seven face characteristics automatically. They chose 20 points among those that associated with BMI and computed automated facial characteristics using the ASM method. After that, the facial geometry and ratio characteristics may be calculated automatically. They employed features normalization for excellent or superior BMI prediction, and statistical learning for the connection between BMI and face characteristics. Least squares regression, Gaussian process regression and Support vector regression are three types of statistical learning [19]. They utilized the MORPH-II database, which contains many face pictures, divided them into two sets: set1 and set2. Based on their findings, they determined that people under the age of ten have smaller eyes and a squarer face, resulting in a higher BMI. People under the age of 20 have a higher BMI because they have a squarer face, smaller eyes, higher brow height, and a smaller ratio of lower face to entire length.

As a result, in this research [20], AI is utilized in BMI interference from face picture to monitor or control weight, and they also built an application, which make their research more relevant to ours. For BMI interference from face images, they utilized deep learning-based Convolutional Neural Network (CNN) architectures [2][20]. They used a variety of models, including VGG architecture for feature extraction because it contains a max-pooling layer, ResNet, DenseNet for feature reuse and propagation, MobileNet, and lightCNN for filtering each convolution layer to force each layer to preserve compact feature maps on their training. They used the Bollywood, VIP-Attribute, and VisualBMI datasets for the face pictures and comparison, as well as other essential information from the web [20]. They utilized the Mean absolute error equation (eq. 1) [20] to calculate the difference between the ground and the BMI estimated by the system.

$$MAE = \frac{\sum_{i=1}^{n} |B\hat{M}I_i - BMI_i|}{n} \tag{1}$$

Their research has one flaw: Their extended CNN cannot be statistically validated by comparing it to a huge face dataset collected by their mobile devices from people of all ages and races. As a result of their study, they have not said if their Android system or application would support all mobile operating systems so that everyone may profit from it.

One of the key research that corresponds to our research is “Predicting Obesity Using Facial Picture during Covid-19 Pandemic” [1]. This study provides a means for anyone who is overweight or obese to seek aid from the comfort of their own homes, based on the current Covid-19 pandemic, which has made it difficult for those with obesity to get the help they need. Their research, like ours, focuses on calculating a person's BMI to see if individuals are overweight, underweight, normal, or obese. They gathered 2D face pictures from Caucasian and African ancestry volunteers to calculate the PAR, WHR, and CJWR, as these features are linked to weight [1][16][18]. They applied a computational method to a face image

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

of African, white ethnicities and were able to apply multiple points on the face image with the application of face detection, resulting in all 7 facial features measures [21]. They discovered that BMI is linked to face features, especially lower facial curvature. They also looked at the elements that help facial models predict body fat measurements and how they could be employed in telemedicine. Based on the cluster of information or anthropometric data they collected and the procedures they used, they were able to obtain everyone's height, weight, BMI, waist-to-hip ratio, and other anthropometric data and tools. However, one of their study's limitations is that not everyone has all of the necessary equipment's to calculate their obesity status using their smartphone.

The work of the authors in [22] made significant contribution impact to this study. To the authors, face characteristics include or explain many aspects of a person's personality, such as social intercourse for expressing identification and sentiments. They investigated different approaches connected with face identification in digital pictures and created a robust face detection system as part of their study. Their system has a substantial influence on face identification, head-pose estimation, facial expression recognition, and human-computer interaction. They developed an active shape model for the features shape model, which focuses on higher level appearance of features and complicated non-rigid characteristics like actual physical, which automatically find landmarks to characterize the form of any modelled item in an image. By initializing the closeness around a head boundary, the genetic active contour "Snake" is utilized to detect head borders. The RGB, YCbCr, and HIS colour space models were utilized for face detection. They utilized the Eigen faces technique to align and normalize the facial picture. They also employed SVMs to recognize faces, which minimize the upper bound on every classification error of the unseen test pattern. As a result, for the sake of computation and detection efficiency, a comparative study of features-based approaches was used.

3. RESEARCH DESIGN

The design science research methodology (DSRM) by [23] was used in the design and development of this research. It consists of six (6) steps as shown in the first column of table 1. How the methodology is applied to this research is explained in column 2 and the output from each step from our research using the methodology is shown in column 3.

Table 2. DSR methodology applied to the research

DSR steps	DSR applied to research	Output to next step
1. Identified problem and motivate for solution	A literature review was done out using Systematic review method according to [40]. The summary of the review is shown in table 1.	Objectives of the research.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

DSR steps	DSR applied to research	Output to next step
2. Define Objectives of a Solution	The objectives of this research are to: 1. Identify research gap in mobile application to obesity determination. 2. develop a mobile application using facial extraction techniques. 3. test the application for accuracy and robustness.	The schematic diagram in figure 3 and 4.
3. Design & Development	The BMI data in figure 1 was used by the software to classify obesity. The software was developed using Java programming language. DSRM was Object-Oriented Analysis and Design (OOAD) methodology with a specific method known as Rapid Application Development (RAD) which enables the researchers to develop software prototypes for BMI determination using facial features as BMI is closely connected with eye-detailed information such as the anterior corneal curvature (ACD) and intraocular pressure (IOP). BMI is also related to a person's neck circumference as well as physical measures or features of the face, such as the cheek-to-jaw-width ratio (WJWR), the width-to-height ratio (WHR), and the perimeter-to-area ratio.	A mobile App source code developed using Java but has not be test run.
4. Demonstration	The body and facial statistics of five participants (identified as Person1 to Person5) who were students/course-mates of the researchers at the North-West University volunteered and their details were used to test the application. All personal or identifying information related to participants were not collected as they were not necessary. The participants were aged between 23-30 and they were also asked to share their dietary pattern and behaviours, and this was helpful in the dietary recommendations. All participants were required to visit the university hospitals in November 2021 for Anthropometric measurements of their height and weight, which were taken three (3) times for increased precision and reliability. Everyone was instructed to remove their shoes, face forward, relax their shoulders, back facing the wall, and align their head up to be measured using the stadiometer (SECA 213)	A mobile App developed and tested.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

DSR steps	DSR applied to research	Output to next step
	in standing posture. As a result, their weights were determined using a DQUIP Scale Mechanical Grey (130kg) and everyone was compelled to wear only the bare minimum of clothing (less heavy clothes). We used people under the age of 30 (this experiment was performed in a school environment and the participants were students).	
5. Evaluation	The test run was repeated three times and the results compare with a desk-checked result and the differences were noted.	An efficient mobile app desk-checked The app generated output was desk-checked with the results obtained through manual computation and there were very insignificant variation in the results obtained which shows that the system performed as expected.

In other to calculate user body mass index (BMI), eq. 2 is used from the research by [21]:

$$BMI = \frac{\text{Weight (kg)}}{\text{Height}^2\ (m^2)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

We used figure 1 to compare and tie each participant's unique BMI calculated from eq. 2 to their nutritional grade to ascertain their obesity status.

Figure 1. Obesity classification according to BMI [7]

The face to BMI front-end representation, or Graphic User Interface (GUI), is shown in figure 2 where the user will be asked to snap a picture of their face. Before taking a picture, the user should ensure that they are facing the camera

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

correctly with their face up (no smile), motionless (don't move), and in bright environment for the software to accurately detect their face.

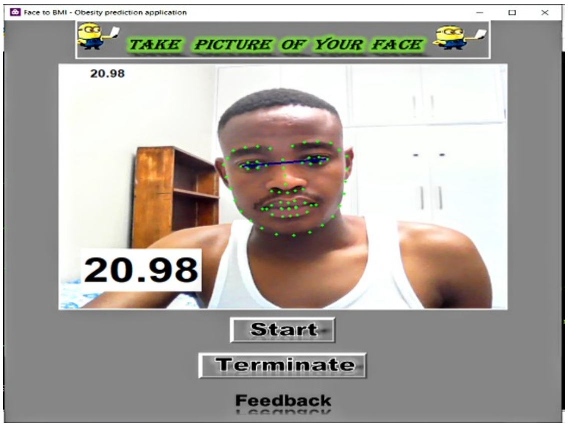

Figure 2. Screenshot of Face to BMI application | GUI (Face detection)

Insufficient lighting will alter the BMI reading provided by the system and in some cases, the system will fail to detect the face and hence no BMI will be computed. It is important the user stay alone when using the system as the program only requires one participant at a time. When more faces are recognized from the background, the program will apply the extraction approach to all the faces but only deliver one BMI value, leaving no way of knowing who the BMI is computed for. It is also recommended that the user removes their spectacles and earrings, refrains from wearing cosmetics or masks, and does not wear anything on their head. The system will execute accurately when these are conditions adhered to. When the user presses the start button, the software will proceed through the steps shown in Figure 3. The user can then click the Feedback button after receiving their BMI value, which will access the relevant website based on the category of their BMI value. Figure 2 depicts the content that will be on the website and is further discussed below. When the user is through with the software, they can press the Terminate button to close or exit it.

Figure 3. Schematic diagram for the prediction of BMI from facial Image.

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

In-depth analysis of the application's testing algorithms. The user will be asked to take a picture of their face, after which the algorithm will perform face detection, looking for all possible facial features such as the width to upper facial height ratio (WHR), cheek to jaw width (WJWR), perimeter of area ratio (PAR), lower face to face height ratio (FW/FH), and mean of eyebrow height (MEH) using facial measurements such as the iris, mouth corners, eyebrows, and nostril [1]. These requirements therefore invalid the photo of animals and other objects other than human. The algorithm will perform Active Shape Model (ASM) fitting for face analysis and improved position for each point in the face after face identification. We utilized the shape predictor 68 face landmarks trained model file from the dlib package for the facial landmarks. Face landmarks, which represent and locate various regions of the human face, were used to make our application more robust. The application will next perform Geometry/Ratio feature extraction to describe the human face shape and its components, such as face texture, before running a regression function to depict the relationship between BMI values and facial measures. We created equations and used regression function as suggested for the prediction of weight and height from geometric elements such as points on the face and corner features. Equation 2 was used to calculate BMI using anticipated weight and height from ASM points, regression function, and geometric points. We used figure 1 to locate everyone's status and determine whether they were underweight, normal, obese, or severely obese based on the BMI calculations. Each obesity status is link to a recommendation page for further information which includes suggestions, doctor recommendations, what to do, and who to consult should counselling be required. The recommendation page flowchart is shown in figure 4 for each of the obesity status.

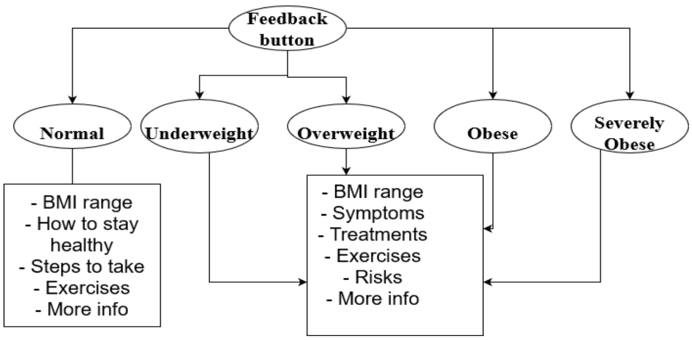

Figure 4. Schematic diagram showing recommendation for each obesity status using the feedback button

4. RESULTS AND DISCUSSION

Table 3 shows the results from of the five (5) participants (one female and four males), which consist of their weight, height, BMI, and their relative BMI status.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

From the table, most male weights were similar, however the females had a greater weight reading. With height, each participant different. Following these measurements, all males' BMIs ranged from 18.5 to 24.5, indicating that they were normal, whereas the female had a higher BMI, indicating that she is more likely to be overweight. Table 4 shows the aggregate readings of each participant after three (3) trials. According to the results of table 3, there is only a minor variance in the readings due to human error, but the readings are otherwise identical. From the results, only the female is overweight.

Table 3. Results obtained from 5 participants

Participants	**Gender**	**Weight** (kg)	**Height** (m)	BMI (kg/m^2)	**Status**
Person 1	Male	45.6	1.56	18.8	Normal
Person 2	Male	50.2	1.51	22.3	Normal
Person 3	Male	55.6	1.60	21.7	Normal
Person 4	Male	42.8	1.53	19.0	Normal
Person 5	Female	58.7	1.50	26.1	Overweight

Table 4. Overall results after three (3) trials from all participants

Participants	**Gender**	**Weight** (kg)	**Height** (m)	BMI (kg/m^2)	**Status**
Person 1	Male	45.2	1.55	18.8	Normal
Person 2	Male	51.1	1.51	22.4	Normal
Person 3	Male	55.8	1.60	21.8	Normal
Person 4	Male	44.7	1.53	19.1	Normal
Person 5	Female	59.4	1.50	26.4	Overweight

The same participants were used for all the readings. The result for each participant is shown in table 5 and when the application is used to conduct the experiment for three consecutive trials to determine the efficiency of the application, the results obtained is shown in table 6 which indicated that there are no significant changes in the results after the three trials. According to the results shown in table 7, the application gave similar results to the experiment conducted manually (practical) as those who had different BMI in our application compared to that of the practical could be because of minimizing the squared error to increase the accuracy and robustness of the application.

Table 5. Results obtained from using the application.

Participants	**Gender**	**Capsize**	Regr_**BMI** (kg/m^2)	Final_**BMI** (kg/m^2)	**Status**
Person 1	Male	334.3863	18.32	19.39	Normal
Person 2	Male	334.2063	22.00	22.01	Normal
Person 3	Male	333.9493	21.09	21.16	Normal

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

Participants	Gender	Capsize	Regr_**BMI** (kg/m²)	Final_**BMI** (kg/m²)	Status
Person 4	Male	335.0586	20.00	19.19	Normal
Person 5	Male	342.0835	25.99	26.03	Overweight

Table 6. Overall results from using the application after 3 trials.

Participants	Gender	Capsize	Regr_**BMI** (kg/m²)	Final_**BMI** (kg/m²)	Status
Person 1	Male	334.3452	18.39	19.38	Normal
Person 2	Male	334.2554	22.10	22.03	Normal
Person 3	Male	333.8454	21.12	21.12	Normal
Person 4	Male	335.0999	20.10	19.16	Normal
Person 5	Female	342.0356	25.98	26.00	Overweight

Table 7. Overall BMI results **comparison** from practical and our application.

Participants	Gender	**BMI** (kg/m²) **Practical**	**Application**	**Overall Status**
Person 1	Male	18.8	19.38	Normal
Person 2	Male	22.4	22.03	Normal
Person 3	Male	21.8	20.02	Normal
Person 4	Male	19.1	21.16	Normal
Person 5	Female	26.4	26.00	Overweight

5. CONCLUSION AND FUTURE WORK

The mobile app from this study requires only the face to be captured directly by the app to calculate the BMI of the user and to determine whether the user is obese or not. Such an app became necessary due to the restrictions on movement and hospital visitation that accompanied the COVID pandemic. The BMI readings from the app are not substantially different from those obtained by doctors using various equipment in the hospitals which is one of the key expectations, implying that the app is accurate and dependable. The use of the app will aid in eliminating overcrowding in hospitals because of weight, height, BMI, and obesity issues. Consequently, doctors will have more time available to attend to more life-threatening issues. In future, we hope the availability of large dataset, machine learning both (supervised and unsupervised), can be used so that the machine can learn and then be able to make predictions about obesity with little human intervention. Our study's limitation is that our model predicted weight and height based on SVM points, which means that while individuals may have the same SVM points, they may not have the same weight, height, or BMI. Another limitation of our study is that light has an impact on BMI readings, when the light is not bright

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

enough for the application to recognize the face, the application may produce false readings.

REFERENCING

[1] A. Chanda and S. Chatterjee, "Predicting Obesity Using Facial Pictures during COVID-19 Pandemic," *BioMed Research International,* vol. 2021, p. 6696357, 2021/03/12 2021.

[2] H. Momin and J.-R. Tapamo, "Automatic Detection of Face and Facial Landmarks for Face Recognition," Berlin, Heidelberg, 2011, pp. 244-253.

[3] L. Di Renzo, P. Gualtieri, F. Pivari, L. Soldati, A. Attinà, G. Cinelli*, et al.*, "Eating habits and lifestyle changes during COVID-19 lockdown: an Italian survey," *Journal of translational medicine,* vol. 18, pp. 1-15, 2020.

[4] C. Bonnet, P. Dubois, and V. Orozco, "Household food consumption, individual caloric intake and obesity in France," *Empirical Economics,* vol. 46, pp. 1143-1166, 2014.

[5] N. L. M. Noor, N. Noordin, F. M. Saman, and N. I. M. F. Teng, "Predicting Obesity from Grocery Data: A Conceptual Process Framework," in *2016 6th International Conference on Information and Communication Technology for The Muslim World (ICT4M)*, 2016, pp. 286-291.

[6] T. Kelly, W. Yang, C.-S. Chen, K. Reynolds, and J. He, "Global burden of obesity in 2005 and projections to 2030," *International journal of obesity,* vol. 32, pp. 1431-1437, 2008.

[7] WHO, "Obesity and Overweight," 2015. [Online]. Available: http://www.who.int/mediacentre/ Obesity and overweight (who.int)

[8] S. Chinchole and S. Patel, "Cloud and sensors based obesity monitoring system," in *2017 International Conference on Intelligent Sustainable Systems (ICISS)*, 2017, pp. 153-156.

[9] L. K. Twells, D. M. Gregory, J. Reddigan, and W. K. Midodzi, "Current and predicted prevalence of obesity in Canada: a trend analysis," *CMAJ open,* vol. 2, p. E18, 2014.

[10] A. Prasad, R. Brewster, J. G. Newman, and K. Rajasekaran, "Optimizing your telemedicine visit during the COVID-19 pandemic: Practice guidelines for patients with head and neck cancer," *Head & neck,* vol. 42, pp. 1317-1321, 2020.

[11] S. Gupta and S. Sood, "Context aware mobile agent for reducing stress and obesity by motivating physical activity: A design approach," in *2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2015, pp. 962-966.

[12] M. Caliendo and W.-S. Lee, "Fat chance! Obesity and the transition from unemployment to employment," *Economics & Human Biology,* vol. 11, pp. 121-133, 2013/03/01/ 2013.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[13] H. Atwa, L. Fiala, and N. M. Handoka, "Neck circumference as an additional tool for detecting children with high body mass index," *J Am Sci,* vol. 8, pp. 442-446, 2012.
[14] C.-H. Tai and D.-T. Lin, "A framework for healthcare everywhere: BMI prediction using kinect and data mining techniques on mobiles," in *2015 16th IEEE International Conference on Mobile Data Management*, 2015, pp. 126-129.
[15] J. Torales, M. O'Higgins, J. M. Castaldelli-Maia, and A. Ventriglio, "The outbreak of COVID-19 coronavirus and its impact on global mental health," *International Journal of Social Psychiatry,* vol. 66, pp. 317-320, 2020.
[16] W. Dietz and C. Santos-Burgoa, "Obesity and its implications for COVID-19 mortality," *Obesity,* vol. 28, pp. 1005-1005, 2020.
[17] S. Djalalinia, M. Qorbani, N. Peykari, and R. Kelishadi, "Health impacts of obesity," *Pakistan journal of medical sciences,* vol. 31, p. 239, 2015.
[18] L. Wen and G. Guo, "A computational approach to body mass index prediction from face images," *Image and Vision Computing,* vol. 31, pp. 392-400, 2013.
[19] G. A. Bray, "Risks of obesity," *Endocrinology and Metabolism Clinics of North America,* vol. 32, pp. 787-804, 2003/12/01/ 2003.
[20] H. Siddiqui, A. Rattani, D. R. Kisku, and T. Dean, "Al-based BMI Inference from Facial Images: An Application to Weight Monitoring," in *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 2020, pp. 1101-1105.
[21] W. Kawohl and C. Nordt, "COVID-19, unemployment, and suicide," *The Lancet Psychiatry,* vol. 7, pp. 389-390, 2020.
[22] A. Kumar, A. Kaur, and M. Kumar, "Face detection techniques: a review," *Artificial Intelligence Review,* vol. 52, pp. 927-948, 2019.
[23] K. Peffers, T. Tuunanen, M.A. Rothenberger, and S. Chatterjee, "A Design Science Research Methodology for Information Systems Research", *Journal of Management Information Systems, 24*(3), 45-77, *2008.*