Research Article

People's fatness and thinness detection using image processing and machine learning

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Abstract

One of the most important priorities in developed countries is the use of machine decision-making instead of a human. One of the areas that need this field is health. For this purpose, determining the obesity and thinness of people can be very useful in studying and examining the health status of a society and adopting health system policies. Images of people as a database of research have been prepared from several different environments where the distance between the camera and the person is the same in all of them. Then, the background of the image is removed using background subtraction. Image features that include image morphological characteristics are extracted from the image and are classified into two categories to perform classification operations. The people were divided into three categories: fat, medium, and thin. The images are noised using the Gaussian low pass filter method with different frequencies filtered using two methods of salt and pepper noise and Gaussian noise. n normal image, the highest accuracy is related to the SVM method with an accuracy of 97.1%, and the lowest is related to the MLP, Bayesian and KNN algorithms, respectively. The results of this paper showed that with the proposed method, in addition to being able to classify the people of a society in terms of obesity and thinness, a higher accuracy was achieved than most of the methods that have been presented so far. According to the solutions and results of this research, by increasing the images of people, in addition to increasing the accuracy, it will reach a more practical level.

Keywords: Classification, Image Processing, machine learning, SVM, Thin, Fat

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1- Introduction

Image processing has become one of the most important sciences of interest to mankind, which has produced tremendous progress in many fields in various ways; in such a way that it has found wide applications in other sciences such as medical sciences, technical and engineering sciences, industrial sciences, basic sciences, etc. and has improved the efficiency, progress, and updating of that science. Image processing has many applications such as shape recognition, image texture recognition, image type, etc. With the rapid development of image processing science and machine learning in theoretical and practical fields, it can be said that the only suitable alternative for decisions based on human vision is the mentioned items. Because the presence of humans in some situations, places, and times, in addition to the cost of human resources, maybe life and financial risks for humans, making decisions with a machine can be a good alternative for this issue. Therefore, in this paper, it is attempted to use image processing-based methods to diagnose the obesity and thinness of a sample of the population without human intervention. Because issues related to the health of humanity are considered one of the issues and problems of every society, attention, and monitoring of health indicators is an important issue for the governance and institutions that are responsible for health, considering that health is closely related to the condition of obesity or thinness of any society. Therefore, measuring, monitoring, and preventing obesity in society leads to the prevention of physical injuries of the people of that society and as a result, a healthier society will be formed physically and even mentally. In the field of monitoring the obesity of people in a society, if human resources for necessary studies sample the samples of society, naturally, in addition to the exorbitant cost and time, this process is faced with serious human errors. Therefore, it is necessary to use a system without human intervention to sample society. Using image processing and machine learning in this field can be a suitable alternative to sampling instead of human labor; in such a way that by using different algorithms of artificial intelligence, training is done once and their results are used for years with the least error, the least cost and the least time. In this paper, we have provided some examples of different people and by using image processing and machine learning, they are divided into three categories: obese, medium, and thin. Finally, by monitoring a society, it is possible to formulate general policies in the field of physical and mental health of the people of that society and prevent the creation of a health crisis in that society. One of the most important public problems that human society is currently dealing with is the problem of obesity and being overweight. The world health organization defines obesity as excessive accumulation of fat or abnormal fat that may harm health. In simple terms, obesity is the result of eating too much and moving too little (Chen, 2015). Obesity is a chronic disorder involving a complex number of environmental, cultural, psychosocial, metabolic, and genetic factors. The prevalence of overweight and obesity in adults and children has reached an alarming level. This trend has been continuously increasing during the prevalence of overweight and obesity and has not stopped (Kim, Kim, Kim, Lee, & Jung, 2018). Therefore, it is impossible to discuss weight loss in society and create physical health in them without monitoring people and estimating their health levels. One of the most important levels of health of individuals as mentioned is the topic of obesity. For this reason, monitoring and measuring the level of obesity in a society is essential to formulate the general policies of a government in the field of health. Monitoring people in society for practical studies for developing the system of letters and policies of the health sector needs accuracy, speed, high quality, and low cost. For this reason, the use of methods based on the use of labor for mentioned reasons is outdated and impractical. For this purpose, the use of machine-based methods, especially artificial intelligence methods, can achieve the goals of accuracy, speed, high quality, and low cost. At the same time, these methods have characteristics such as tirelessness, constant monitoring, low maintenance cost, no need for labor, and high accuracy, which increase the need to use them. Image processing is a method of converting an image digitally and doing some work on it, to get an improved image or extract some useful information from it, which is used in stages such as classification, etc. Many concepts such as computer vision, image processing, machine learning, and others concepts have many similarities together, so there is no precise definition for these concepts, and cannot bind them to a specific area. However, here we will try to demarcate these concepts to some extent and express the actions related to these areas in simple language.

The main goals of this paper are as follows:

• Providing the approach suggested
• Machine learning and image processing modelling.
• Body size identification with high accuracy

This paper is structured as follow in the second part, we examined related works, in the third part, we discussed the suggested approach, in the fourth part, we acquired the proposed method's findings, and finally in the fifth part, we have a conclusion.

2- Literature Review

Machine learning is a developing subset of computing algorithms that aims to imitate human intelligence through environmental learning. In the brand-new era of "big data," they are regarded as the workhorse. Various fields, including pattern recognition, computer vision, spacecraft engineering, finance, entertainment, and computational biology, as well as biological and medical applications, have effectively used machine learning techniques (El Naqa, I., & Murphy, 2015). As reported in (Moharamkhani,Yahyaei Feriz Hendi,Bandar, Izadkhasti, & Sirwan Raza, 2022) Moharamkhani et al. proposed a new approach for intrusion detection in cloud computing environments using a combination of the Firefly Algorithm and Random Forest. Hasanvand et al. (Hasanvand, Nooshyar, Moharamkhani, & Selyari, 2023) proposed a different approach that focuses on identifying vehicles using machine learning and image processing techniques. Used in (Gavari Bami, H., Moharamkhani, Zadmehr, Najafpoor, & Shokouhifar, 2022) Gavari Bami et al. to accurately identify attacks.

Harty et al (2020) proposed a novel method for estimating body fat using machine learning and 3-dimensional optical imaging. The study involved collecting data from 131 participants to develop a predictive model that could accurately estimate body fat percentage based on measurements of body shape and size taken with an optical scanner. The results showed that the machine learning model was able to predict body fat percentage with a high level of accuracy, indicating the potential usefulness of this technology in clinical settings for assessing obesity and related health risks. Ahn et al, (2018) compared different clustering methods for classifying obesity. The study used data from 349 participants, including body mass index (BMI) and other health-related measures, and applied four clustering algorithms to identify distinct groups based on these variables. The results showed that the K-means algorithm performed the best in terms of accuracy and consistency, while the hierarchical clustering method produced more variable results. The authors suggest that the K-means algorithm may be useful for identifying subgroups of obese individuals with different health risks and treatment needs. Uçar et al, (2020) discussed the use of hybrid machine learning algorithms for estimating body fat percentage. The study used data from 200 participants, including measurements of body mass index (BMI), waist circumference, and skinfold thickness, and applied several different machine learning algorithms to predict body fat percentage. The results showed that the hybrid algorithm, which combined the random forest and artificial neural network models, performed the best in terms of accuracy compared to other individual algorithms. The authors suggest that this approach may be useful for accurately estimating body fat percentage in clinical settings and could potentially improve the diagnosis and treatment of obesity-related conditions.

Ferenci et al (2018) explored the use of artificial neural networks to predict body fat percentage using anthropometric and laboratory measurements. The study used data from 160 participants, including measurements of BMI, waist circumference, and various blood tests, and trained an artificial neural network model to predict body fat percentage based on these inputs. The results showed that the model achieved a high degree of accuracy, with a correlation coefficient of 0.94 between predicted and actual body fat percentage values. The authors suggest that this approach may have clinical utility in predicting obesity-related health risks and monitoring changes in body composition over time. Chatterjee Gerdes, & Martinez, (2022) highlight that the prevalence of obesity has increased significantly worldwide, leading to several health risks such as cardiovascular disease, diabetes, and cancer. In this context, identifying the factors contributing to obesity and overweight can help develop effective preventive measures. They conclude that machine learning models offer a promising approach to identify risk factors associated with obesity and overweight, and they can be useful in developing personalized interventions for individuals at high risk for obesity-related health problems. Akman et al, (2022) discussed the use of photoplethysmography (PPG) signals and machine learning algorithms for determining body fat percentage in individuals, based on gender. The research was conducted on a sample population of both men and women and resulted in a reliable model for predicting body fat percentage using PPG signals. This finding can provide a non-invasive and cost-effective method for monitoring body composition in clinical settings.

Hussain Cavus, & Sekeroglu, (2020) proposed a hybrid machine learning model for predicting body fat percentage. The model combines support vector regression with emotional artificial neural networks to improve the accuracy of predictions. The study involved collecting data on body fat percentage, age, height, weight, and gender from 200 participants. The proposed model was trained and tested using this data, and it was found to outperform conventional machine learning models in terms of prediction accuracy. They suggested that this hybrid model haspotential for use in clinical settings for accurately predicting body fat percentage. The published works in this topic will next be compared in Table 1.

Table (1): Comparison of already published works.

Ref	Technic	Accuracy	Precision	F1-score	Recall
Harty etal (2020)	Machine learning and 3-dimensional optical imaging	-	-	-	-
Ahn etal (2018)	Fuzzy rule-based system (FRBS)	P	-	-	-
Uçar etal (2021)	Using hybrid machine learning algorithms	P	-	-	-
Ferenci & Kovacs (2018)	SVM	-	-	-	-
Chatterjee etal (2020)	Machine learning	P	-	-	-
Akman etal (2022)	Photoplethysmography Signal Using Machine Learning Algorithm	-	-	-	-
Hussain etal (2021)	Support Vector Regression and Emotional Artificial Neural Networks	-	-	-	-
Proposed SVM	Using image processing and machine learning	P	P	P	P

3- Method

The first step is to select the images, which after being prepared actions are applied to them. Then the features of each image are extracted, which mainly include measurements. After that, the training and testing phase begins until the result is obtained.

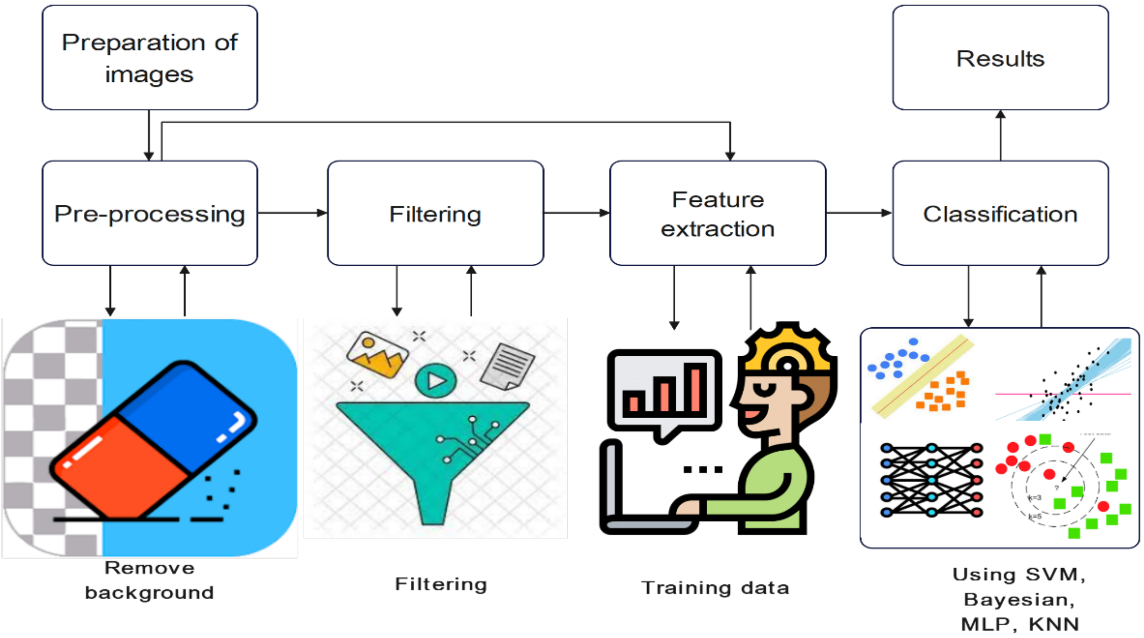

Fig (1): Diagram of image classification steps using machine learning.

Preparing images

Images were prepared using a model camera (Canon13mp) in the free medium without any measures in terms of light and a completely natural and dynamic environment. These images were taken from the same distance (190 cm) from the camera to the person and the angle of the camera to the person is in the same direction. These images are provided in different environments, which will of course increase the level of design verification. Examples of images in each of the three discussed classes (including fat, thin, and medium) have been prepared. As shown in Figure 2.

Fig (1): Diagram of image classification steps using machine learning.

Pre-processing

To find features from images and finally categorize them, a series of pre-processing should be done on the images.

Removing the background

Because the distance and angle of the camera to the person are the same in all the images, the background of the images can be easily removed by using background subtraction, and only the image of the person is kept for the next steps. Such a way that first the background image without a person is prepared and the image is brought to binary mode using a thresholding operation and the same operation is performed for the image with the person. Then, by subtracting two images, the resulting image is an image containing a binary person and, of course, some bubbles, and by using area filtering, the bubbles are all removed and the resulting image is the person's image. Now, by adding the original image of the individual with the binary image of the individual obtained in the previous step, the background is separated. Subtraction also means that each pixel of the original image is subtracted from the corresponding pixel in the background image, and if the result of the image is more than a certain value, then the image is not the background, and if it is less than that, it is the background (Liu, Chen, & Li, 2009)

$$D(x,y) = |f_p(x,y) - f_f(x,y)|$$

$$D(x,y) = |f_p(x,y) - f_f(x,y)| \qquad (1)$$

$$mask(x,y) = \begin{cases} 1 & if D(x,y) \le T \quad background \\ 0 & if D(x,y) \ge T \quad foreground \end{cases}$$

$$mask(x,y) = \begin{cases} 1 & if D(x,y) \le T \quad background \\ 0 & if D(x,y) \ge T \quad foreground \end{cases} \qquad (2)$$

f_p is the background image and f_f is the main image. The value of T is different in color images, but here, since the images are binary, the value of T can be set to greater than one. The operation of removing small holes (bubbles) is also done in such a way that it removes all areas smaller than the smallest possible area that is related to individual pride. Examples of images after background removal are shown in Fig 3.

Fig. (3): Examples of images after removing the background.

In addition to normal images, filtered and noisy images are also studied and investigated. To prepare the filtered image, they have been degraded using a low-pass Gaussian filter with different frequency radius. To create noise, the images were degraded in two stages using salt pepper noise with different densities and Gaussian noise with different frequency radius. Fig 4 illustrates an example of damaged photos with salt pepper noise, Gaussian noise, and a Gaussian filter.

Fig. (4): An example of degraded images with salt pepper noise, Gaussian noise, and Gaussian filter.

After the individual is separated from the whole image, the main operation of classifying individuals by type should be done. For classification, the features are extracted first, and then the classification is done using the features obtained from the feature extraction.

Filtering

The filtered and noisy photos are also analyzed in addition to the regular ones. They were destroyed by using low pass Gaussian filters with various frequency beams to create filtered images. In order to explore the effects of the suggested technique on these photos, images are destroyed in two phases utilizing salt-and-pepper noise with various densities as well as Gaussian noise with various frequency rays.

Feature extraction

In this stage, features should be extracted from images related to people to use these features to categorize. In this research, it is tried to use features that are more related to the measurement of length. These features include:

1. Person's height
2. Waist width
3. Thigh width
4. Shoulder width
5. The area occupied by the person in the image
6. The length of the main diameter of the person
7. The length of the minor diameter of the person

The important thing about these features is that all the sizes in the MATLAB program are measured in pixels. To measure the above characteristics, pre-processing should be applied to the images, the result of which is to find the exact location of the person in the image.

On the other hand, for the calculations of the above features, first, the image is converted to binary mode and then its edges are found by the Sobel edge detection algorithm. After that, by using a suitable filter, the process of broadening and enlarging the edge lines begins, and then with thresholding and again the process of broadening, a normal image with a specific plaque is obtained. Threshold values for the thresholding operation and the amount of broadening are obtained by trial and error. By the SCW segmentation algorithm and by the analysis algorithm, the connected components of the connection points are found. Finally, by applying the area filter, the areas above and below the normal level are removed and the final image contains the person in the actual position of the person. Fig 5 from the right to the left shows the steps of doing the work on a person:

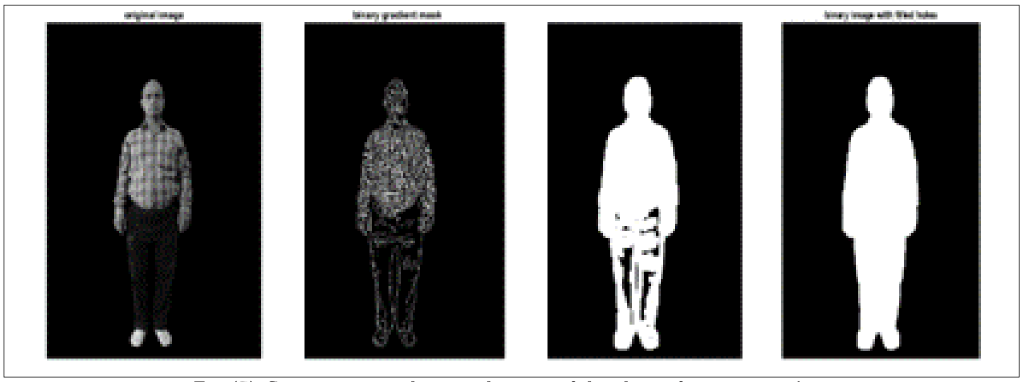

Fig. (5): Steps to extract the exact location of the plaque from a person's image.

After the measurement has been done to determine features, the classification of images is based on the features found.

4- Research Findings

In this dissertation, an evolutionary developmental trajectory is proposed to determine the condition of obesity in images. The main hypothesis of this research was to be able to recognize a person's obesity status independently of human intuition. According to the pictures taken in terms of completely natural memory, results were obtained which will be discussed below. For this purpose, the sizes were used as the characteristics of each image, and classifying them finally led to the determination of the person's obesity status. This algorithm was implemented in different modes that yielded significant results. Before dealing with the results, the type of their graphs will be discussed.

The results of the support vector machine on the raw images

At first, this proposed algorithm was applied to the set of raw images, which includes three classes (fat, thin, and medium). Eight features were considered for each image.

Raw images are images taken directly by the camera and not operational on them. These data were obtained using the process described in the previous chapter. For each class, six samples are considered. The confusion matrix for all classes is depicted in Fig 6.

The numbers inside each square of the main diameter indicate the correct assignment of the classes and the numbers inside the non-diameter squares indicate the wrong assignment of the classes.

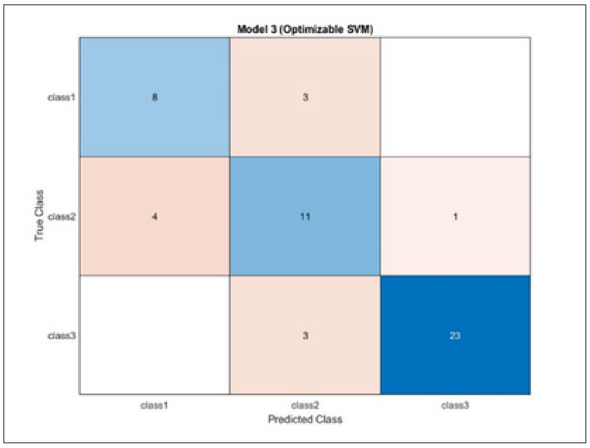

Fig. (6): Confusion matrix related to all classes.

Results of classification of support vector machine on filtered images

The proposed algorithm was applied to the set of filtered images, which includes three classes (fat, thin, and medium). Eight features, such as raw images, were considered for each image. Filtered images are images that have been degraded using a low-pass Gaussian filter with radius of 1000, 500, and 100. Six samples are considered for each class.

Fig 7 illustrates the confusion diagram for the filtered images.

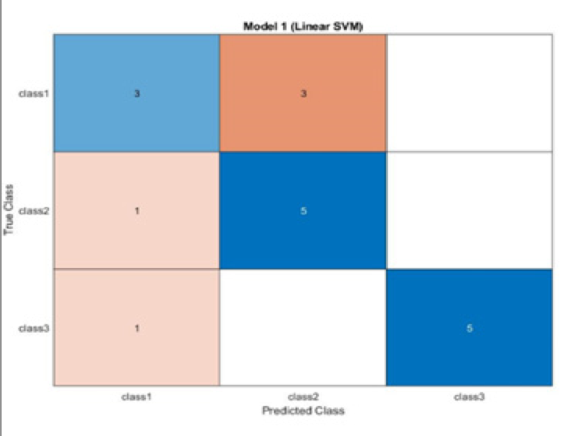

Fig. (7): Confusion diagram related to filtered images.

The results of support vector machine classification on noisy

To check the accuracy of the proposed method, as this method was applied to filtered images, it was also applied to noisy images. For this purpose, the images have been destroyed using salt and pepper noise as well as Gaussian noise. Fig 8 describes the confusion diagram for noisy images.

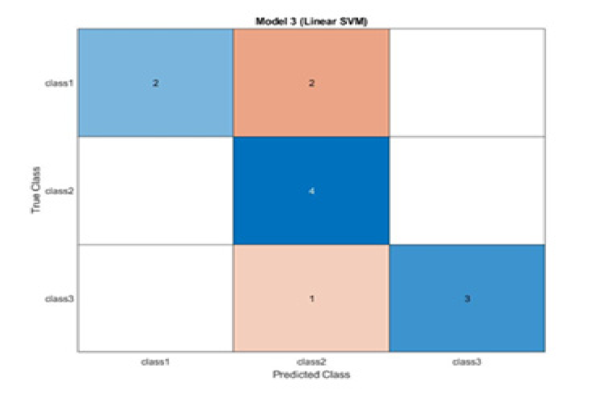

Fig. (8): Confusion diagram related to noisy images.

5- Conclusion

Our research has used machine learning as a classifier. On the other hand, in this research, a Gaussian low-pass filter with different radius and pepper-salt and Gaussian noise has also been applied to the images, the results of which show the high efficiency of this research. The raw images are filtered using the Gaussian method (with available frequency radius) in Table 2:

Table.(2): The amount of frequency radius applied to the images to filter the images.	
The frequency radius's number	The frequency radius's value
frequency radius 1	1000
frequency radius 2	500
frequency radius 3	200
frequency radius 4	100

In addition, the raw images are noised using two methods of Gaussian noise (with different variances) and pepper and salt noise (with different densities). Table 3 shows the values of salt pepper and Gaussian noises:

Table. (3): The amount and type of noise applied to the images to make the images noisy.			
Noise type/noise amount	Noise amount (density or variance)		Unit
Pepper and salt noise	0.1	0.5	Density
Gaussian noise	650	5800	Variance

Table 4 shows the comparison of the proposed solution on normal, filtered, and noisy images with support vector machine learning (Cortes, & Vapnik, 1995), Bayesian (Ruggeri, Kenett, & Faltin, 2007), Multilayer Perceptron neural network (Rosenblatt, 1962., Rumelhart, Hinton, & Williams, 1985) and k-nearest neighbor (Altman, 1992., Hall, Park, & Samworth, 2008)

Table.(4): Comparison of accuracy on normal, filtered, and noisy images with two machine-learning methods.				
Images type/class type	Proposed SVM	Bayesian	MLP	KNN
Normal images	97.1	90.9	92.9	88.6
Filtered images	78.6	77.7	74.3	74.28
Noisy images	82.9	66.7	82.9	82.7

Table 4 shows that the SVM machine learning method has performed better than the other three methods in terms of classification in the 8-feature space. As we see, the SVM method brings high accuracy for raw and noisy images, whereas the KNN algorithm performs well for filtered images. Most successful categorizations occurred in classes 1 and 3, because class 2, which corresponds to average people, is generally close to one of categories 1 or 3. Table 5 compares the performance metrics for various classification techniques. The Proposed SVM algorithm achieved the highest scores in three out of four metrics, making it the best performing algorithm overall. The Bayesian and MLP algorithms showed similar performance across various metrics, while the KNN algorithm performed the worst across all four metrics. Table 5 provides valuable insights into the performance of different machine learning algorithms and can help in selecting the best algorithm for a given task based on its specific requirements.

Table (5): Comparison of the proposed method (SVM) with other efficient methods.

Algorithms	Accuracy	F1-score	Precision	Recall
Proposed SVM	97.1	98.23	98.74	95.63
Bayesian	90.9	89.61	91.83	88.49
MLP	92.9	91.84	91.52	91.33
KNN	88.6	88.21	87.7	89.48

According to the application of classification, increasing the accuracy of classification in this field can be considered. On the other hand, the ease of performing those methods in terms of science can be discussed. For this reason, in this research, in addition to using the scientific methods of the subcategory of machine learning, some work was also done to increase the final accuracy level of the classification. For this purpose, the images were prepared in a dynamic environment and then the background was separated by subtracting the background. The desired features, which include eight items, were extracted from the resulting images. Finally, as mentioned, the final accuracy of our proposed method with the SVM algorithm was 97.1%, which has relatively higher accuracy.

There are a number of potential future research projects that might be taken into consideration based on the findings and outcomes of this study. First, more research into the application of computer decision-making in many industries, particularly in healthcare, can be investigated. This study focused on categorizing patients according to their obesity and leanness, but machine decision-making may also be successfully used in other healthcare settings. Second, adding additional photographs of people to the database and undertaking in-depth research could improve accuracy. Although a database of photographs from various environments was employed in this study, more images and the inclusion of images from various populations could perhaps boost the classification system's accuracy. Third, looking into different techniques for image processing noise reduction can also be taken into consideration. There may be alternative ways or combinations of techniques that could produce better results than the Gaussian low pass filter method used in this study with two noise filtering methods. At last it is possible to investigate the potential advantages of this classification technique for creating health policies and advancing public health. This study showed the value of categorizing people according to their obesity and thinness status, but more research is needed to determine how to utilize this data to develop efficient health policies and programmer to deal with these problems.

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