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BODY MASS INDEX INFERENCE USING FACIAL FEATURES AND MACHINE LEARNING ALGORITHMS

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Abstract: The proposed health care system, which employs Kinect as well as data mining technologies with a view of conveniently predicting BMI using facial images. The integration of face detection and feature extraction by means of Haar cascade is aimed at collecting the necessary information about the face. In this regard, the framework uses machine learning algorithms for data mining such as data preprocessing, extraction, evaluation and presentation to assist in training models that are used for predicting obesity levels (classification), body weight and fat percentage levels (regression) based on different parameters. For instance, it acts as a platform for investigating body weights more comprehensively thus helping paralyzed or critically ill patients who cannot be subjected to normal means of emergency medical services measurements.

Index Terms - Body mass index (BMI) ,Facial features, BMI prediction ,Machine vision Large database, cardiovascular risk, BMI, young adults.

I. INTRODUCTION

Several lifestyle and physiological factors significantly affect the development of cardiovascular diseases (CVD), including dietary habits, levels of physical activity, smoking behavior These factors collectively contribute to the development of dyslipidemia, hypertension, glucometabolic disease, obesity and a large share of global mortality and age loss occur to disability Rapanam, The close global jokes associated with CEVD-Jokhima have been classified as blood in blood with glucose, body rest, or fat is discouraged, especially in the young, where the vasculature is common and uncomplicated -the rhythm of the heart in the first stage of heart failure is weak. The methods are important

Risk assessment is a key component in the prediction of CVD progression, allowing the identification and evaluation of treatment guidelines and the implementation of primary and secondary prevention strategies, ultimately aimed at them eyes to reduce medical costs Risk assessment protocols provide a valuable tool for estimating 10-year risk of cardiovascular events, with factors including sex, age a diet, body fat, blood pressure, and smoking status Although the SCORE program primarily targets individuals over the age of 40, the Framingham Risk Score applies to younger populations by factors such as age, HDL cholesterol levels, hypertension, hypertension treatment, smoking status , etc. upon consideration.Comparisons of risk assessment systems vary in sensitivity and specificity publish, and SCORE and Framingham Risk score demonstrating distinct predictive accuracies.

The focus of the present study was to investigate the association between body mass index (BMI) and cardiovascular risk assessment in young people in the prevention of early cardiovascular events This study aimed to provide the role of BMI as a potential predictor of cardiovascular risk is clear.Decoding facial expressions is a long-standing project, of interest to psychologists, sociologists and computer scientists, because human faces carry infinite information about identity, emotions, age a of one's appearance, gender, race, attractiveness, and personality traits Let's aim to do it. BMI is an important measure of body fat, where Gallagher et al. expressing his position in this matter. Additionally, BMI is important as a visual descriptor of individuals, especially in terms of addressing overweight problems, as highlighted by Andrew et al. who linked BMI to the risk of various adult cancers.

Traditionally, calculating BMI involves measuring body weight and height, thus requiring tools such as rulers and scales. The method of calculating BMI is simple, by dividing the weight (in kilograms or pounds) by the square of the height (in meters or inches), the categories are adjusted.

$$\mathbf{BMI} = \begin{cases} \dfrac{weight(kg)}{height(m)^2} \\ \quad or \\ \dfrac{weight(lb) \times 703}{height(in)^2} \end{cases}$$

They are divided into four categories—internal underweight, underweight, overweight, and obese—BMI values correspond to specific areas, providing a broader understanding of a person's weight status Figure 1 Visually models facial images corresponding to different BMI categories, and provides a visual representation of different weight statuses in the population studied This study involves the use of facial imaging to estimate BMI, which can measure obesity and associated health risk Provides a noninvasive and accessible tool

Fig1: Some facial images display varying BMI values and corresponding categories. As the BMI increases, noticeable increases in facial adiposity become evident.

Body mass index (BMI) serves as a metric for assessing an individual's weight relative to their height. This measurement is derived by dividing the weight in kilograms by the square of the height in meters. In short, BMI provides a quantitative evaluation of body composition.

Calculating BMI traditionally requires physical measurements and specific equipment, which is somewhat uncomfortable. However, a promising proposal in the healthcare industry is to change this pattern through the use of new technologies and data analytics techniques. The idea is to calculate BMI based on facial photos.

This proposed system includes facial recognition sensors and feature extractors, and uses sophisticated algorithms to recognize relevant facial information. It aims to analyze these facial images through machine learning and predict not only obesity rates but also body weight and fat percentage using a variety of parameters

The potential impact of such a system is substantial, especially for individuals who may have difficulties with traditional measurement methods due to health conditions or disabilities and can facilitate the BMI screening process especially in requiring clinical settings in an emergency where rapid investigation is needed.

Now, let's examine the broader context of obesity. According to research published by the GBD 2017 Obesity Collaborators, more than 4 million people die each year from complications related to excess weight. Paradoxically, the prevalence of obesity has increased in recent decades, affecting both children and adults worldwide.

Of particular concern is that the burden of obesity is not limited to developed countries; Low-income and developing countries are also struggling with rising rates. In fact, the overall infection rate in these areas is a staggering 30% higher than the rate in developed countries.

The consequences of obesity go beyond physical health issues. Although there is no direct link between emotional health and obesity, the social and psychological consequences can be significant. Isolation, low confidence, mood disorders and eating disorders are some of the challenges that individuals may face.

Medically, obesity causes many conditions including type 2 diabetes, high blood pressure, cardiovascular diseases, asthma and other respiratory diseases, as well as back pain and other musculoskeletal problems. Specifically, by utilizing new technologies and data-driven approaches, we not only have the potential to improve the accuracy and accessibility of BMI assessment, but we can overcome multifaceted challenges many causes of obesity worldwide are also addressed.

II. RELATED WORK

Recent research in psychology and human emotions has shown that facial features are associated with body mass index, or BMI. These studies investigate the association of specific facial characteristics with BMI, shedding light on the complex interaction between facial structure and body weight

For example, Coetzee et al. conducted a study with 84 Caucasian participants, carefully photographed their faces, recorded biometric data such as weight, height, and blood pressure and then recruited additional controls to indicate perceived weight on these face photographs. The findings highlighted the power of facial fat to predict health and perceived attractiveness.

In another study, Coetzee and colleagues analysed three distinct facial features in 95 Caucasian-99 participants—width-to-height ratio, cross-sectional-to-height ratio, and face and jaw width Equation The calculation was done. Results revealed a significant association between these facial features and BMI, and gender differences were observed.

Similarly, BMI of the seven frontal quadrants in Korean individuals of different ages. Their study included 911 people in their twenties and sixties. By carefully recording facial features and estimating Pearson correlation coefficients, interesting relationships between facial characteristics and BMI were found, providing insight into age-specific patterns.

Overall, these studies highlight the complex relationship between facial morphology and body weight, providing valuable insights that may inform future research and clinical interventions in which they aim to understand and address obesity-related issues.

In addition to the findings in psychology and human emotion research concerning the relationship between facial features and BMI, an emotionally expressive relationship is evident in some faces such that, analysing faces includes BMI of corresponding types which, as illustrated in Figure 1, we almost exclusively visual inspection We can study the clues about a person's fat levels

Based on these insights from psychology and our observations, there is a compelling argument to investigate a computational method for predicting BMI from facial images is not that such a method can provide the findings in psychology research have not only been validated but also offer the advantage of scalability using large datasets. Unlike psychology studies, which typically involve a limited number of facial images, the computational approach allows for the analysis of large amounts of data, thereby increasing the robustness of the findings

Additionally, whereas psychology relies on manual coding of facial features, which is inherently limited by the size of the data, computational methods can automate this process and has greatly facilitated large-scale research, where existing psychosocial research on the relationship between facial features and BMI focuses on clarity, there goes our computational approach further by calculating BMI directly from facial images

The main advantage of BMI estimates from facial photographs is their non-invasiveness. Traditional methods of BMI calculation require accurate measurements of height and weight, which may not always be possible, especially for information such as online photographs or surveillance videos with faces only information is available. For example, in online dating or friend finding sites where only facial images are displayed, automatic prediction of BMI from facial images can be a valuable tool for evaluating physical attractiveness and health status

Assessing cardiovascular risk is essential for identifying risk factors and guiding therapy for cardiovascular diseases (CVD). It plays a critical role in both primary and secondary prevention, encouraging individuals to adopt healthier lifestyles or treatments. While direct methods such as risk prediction algorithms are effective for short-term assessment, indirect methods like using BMI and resting heart rate are becoming popular for long-term preventive measures. Nevertheless, ongoing research is being conducted to evaluate the effectiveness of these methods.

BMI and resting heart rate are commonly used indicators for cardiovascular risk assessment. While there is ongoing debate about the relationship between BMI and overall risk of death, obesity is widely linked to adverse changes in atherosclerosis risk factors. Overweight individuals are at an increased risk of type 2 diabetes, hypertension, and dyslipidaemia. Maintaining healthy eating habits and engaging in physical activity are crucial for managing body mass and reducing CVD risk, especially among young adults.

In cardiovascular disease anticipation, it is important to start assessing cardiovascular risk from adolescence and to educate individuals about the importance of maintaining a healthy lifestyle. This includes promoting best practices and removing barriers to maintaining a healthy body. Overall, the findings highlight the importance of interventions to prevent cardiovascular disease and promote overall health.

The study highlights the importance of early cardiovascular risk assessment and intervention, especially in young adults, to promote cardiovascular health. Effective communication strategies are needed to raise public awareness and promote best practices. However, the limitations of the study underscore the need for further research to enhance our understanding of cardiovascular risk factors and improve prevention programs.

In summary, by using computational methods to predict BMI from facial images, we not only validate and extend psychosocial research findings but also open up new possibilities results for non-invasive health research in a variety of practical applications, from online platforms to surveillance systems.

III. METHODS

1. Approach:

- Participants completed demographic and clinical questionnaires after receiving an explanation of the aims and rules of the study.
- Participation was voluntary and anonymous.
-Registered nurses performed health measurements.

2. Participants:

- Conducted a cross-sectional study among university college students in Lublin, Poland.
- A convenience sample was taken using a stratified random-group method.
- In the academic year 2008-2009, there were 11 university colleges with 85,911 students, making Lublin the sixth largest education center in Poland.
- Out of 2000 students selected, a total of 1593 full-time students volunteered to participate in this study.

3. Reviews:

- Blood pressure: measured oscillometrically with Omron M1 Classic model. After a 10-min break, three readings were taken and the average recorded.
- Anthropometric measures: Body weight and height were measured using a standard medical scale and an altimeter. Body mass index (BMI) and waist circumference (WC) were calculated accordingly.
- Biological health indicators: Fasting lipid panel analyzes included total cholesterol (TC), HDL cholesterol (HDL-C), LDL cholesterol (LDL-C), and triglycerides (TG) Determined based on acceptable thresholds unsaturated cholesterol.

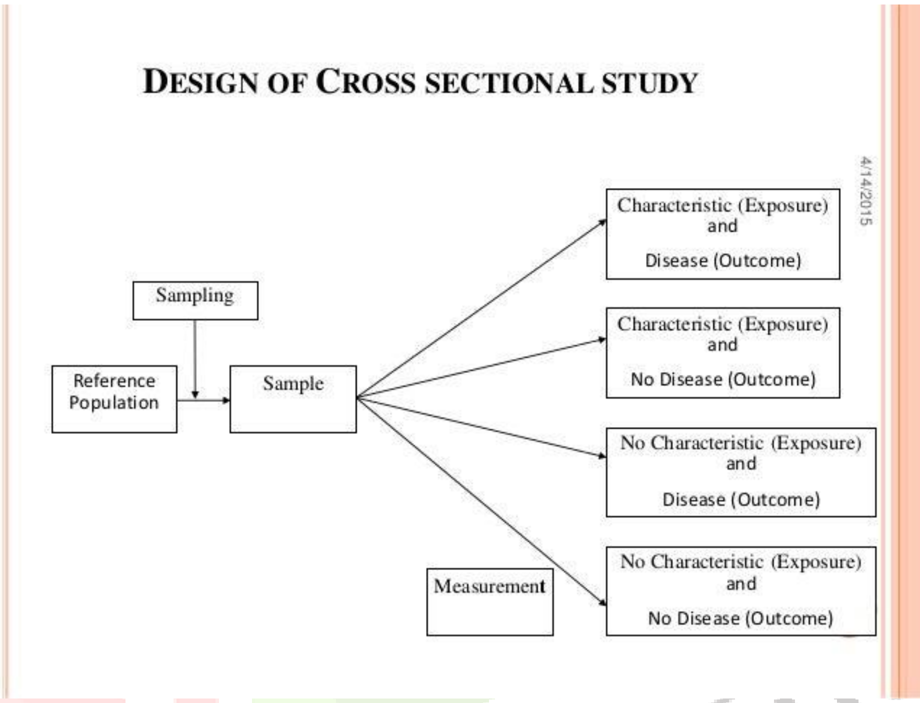

Fig 2: Plan and group selection diagram for cross-sectional survey

In summary, the study collected data on cardiovascular risk factors among university students in Lublin, Poland, using standardized methods of measurement and analysis These included blood obesity, demographic and biological health indicators of fat levels.

Overall cardiovascular risk assessment:

- The Framingham Risk Score (FRS) was used to estimate 10-year cardiovascular risk. The tool uses data from the Framingham Heart Study and is designed for adults age 20 and older who do not have heart disease or diabetes. It considers factors such as gender, age, cholesterol, smoking status, blood pressure, and antihypertensive medications.

Research questions:

- The screening queries encompass a range of factors including age, gender, place of residence, smoking habits, and medical history (such as heart disease, hypertension, diabetes, and family history of heart disease).

Statistical analysis:

- The statistical assessment entails identifying measurable parameters utilizing median values and standard deviations, while non-measurable ones are assessed through percentiles. The Pearson correlation test is applied to normally distributed variables, and the Spearman test is employed for variables that are not normally distributed, assessing relationships between variables. Statistically significant correlations are determined with a p-value of . Analyses were conducted using the STATISTICA 8.0 software.

Opinion of the Bioethics Commission:

- The research was conducted as part of a project funded by Lublin Medical University, with the research grant designated as PW 676/07-10.

IV. SYSTEM ARCHITECTURE

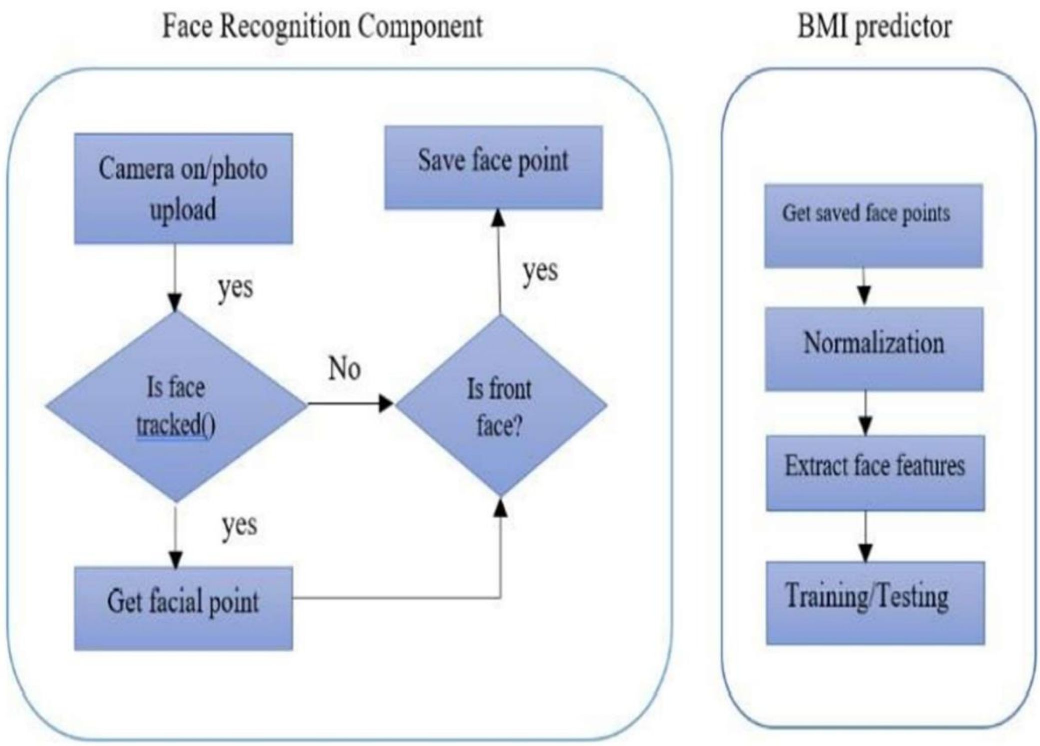

Figure 3. System Architecture of the ML-Based BMI Detection System using Facial Recognition

Figure 3 refers to an image of a face recognition aspect system with various steps such as storing facial points, uploading images, extracting facial features, the training/testing process etc. It also includes features such as BMI predictor , camera, facial normalization and tracking.

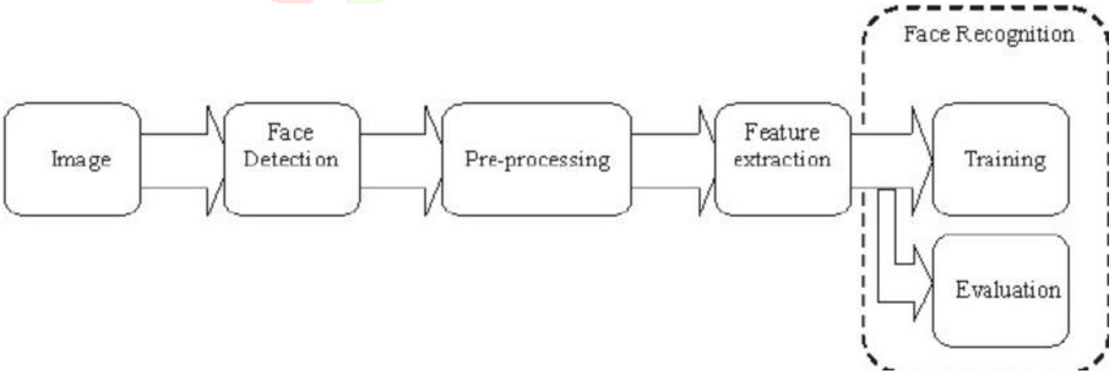

Figure 4. System Architecture of the ML-Based BMI Detection System using Facial Recognition

The figure 4 are referring to seems to be a facial recognition system. I'll break down each component and its functions:

1. Foreground: This represents the main input to the system, which is the image of the foreground that needs to be seen.

2. Image: This is the raw input image of the face that should be visible. It can be captured from a variety of sources, such as cameras or uploaded images.

3. Pre-processing: Pre-processing is the first step in improving the image quality. This can include functions such as noise reduction, adjusting lighting conditions, and adjusting the image size to ensure uniform images.

4. Recognition: involves the identification of a face within an input image, encompassing the determination of its position within the image. This crucial step aids in distinguishing the foreground, specifically the face, from other background elements present in the image

5. Extraction: Once a face is identified, the next step is to extract the appropriate features. This typically involves identifying distinctive facial landmarks, such as eyes, nose, and mouth, and extracting the numbers (objects) that define these landmarks Some common feature extraction methods and methods such as principal component analysis (PCA) or deep learning-based feature extraction networks .

6. Feature: This represents a numerical representation or feature extracted from a known face. These features are basically perfect representations of a face that captures its unique character.

7. Training: In the training phase, the system learns to recognize faces based on the extracted features. This involves feeding the extracted features into a machine learning model or algorithm and changing its parameters through a process called training. During training, the model learns to associate particular objects with familiar objects.

8. Evaluation: Once the model is trained, it should be tested to evaluate its performance. Analysis involves testing the model on a separate set of images (not used in training) to measure the accuracy and effectiveness of face recognition This step helps identify any limitations or areas for face improvement seeing through the system.

Overall, the figure illustrates the mechanism of tasks involved in a face recognition system from preprocessing, detection to feature extraction, training, and evaluation Each phase plays an important role in the overall operation of the system, and ultimately provides faces can be correctly recognized in input images.

V. UML DIAGRAMS

The angles and distances from which photographs are taken can have a significant impact on the face features captured. To obtain relevant facial features, we must first identify valuable images, such as the frontal face, and then do normalization, such as rectification of the slanting face. Many other characteristics, including gender, age, and human DNA, will have an impact on the relationship between facial curves and BMIs. As a first step, we want to create a basic BMI prediction system so that we can collect additional data. We used Keras Application Programming Interface (Keras API) to create this BMI prediction model. Keras is a Python- based neural network Application Programming Interface (API) that is tightly linked with TensorFlow (a machine learning framework). This model provides a straightforward, user- friendly method of defining a neural network, which TensorFlow will subsequently construct for the user. TensorFlow is a set of open-source frameworks for developing and dealing with neural networks, such as those used in ML and Deep Learning applications. Convolutional Neural Network(CNN) is the algorithm utilized in this research. CNN is a Deep Learning system that can take an input picture, give relevance (learnable weights and biases) to various aspects/objects in the image, and distinguish between them.

5.1 Use Case Diagram:

- Use case diagrams illustrate the system's functionalities from a user's perspective.
- It identifies the different actors (users, systems, or external entities) and their interactions with the system.
- Use case diagrams depict the high-level system requirements and the main tasks or actions performed by the users.

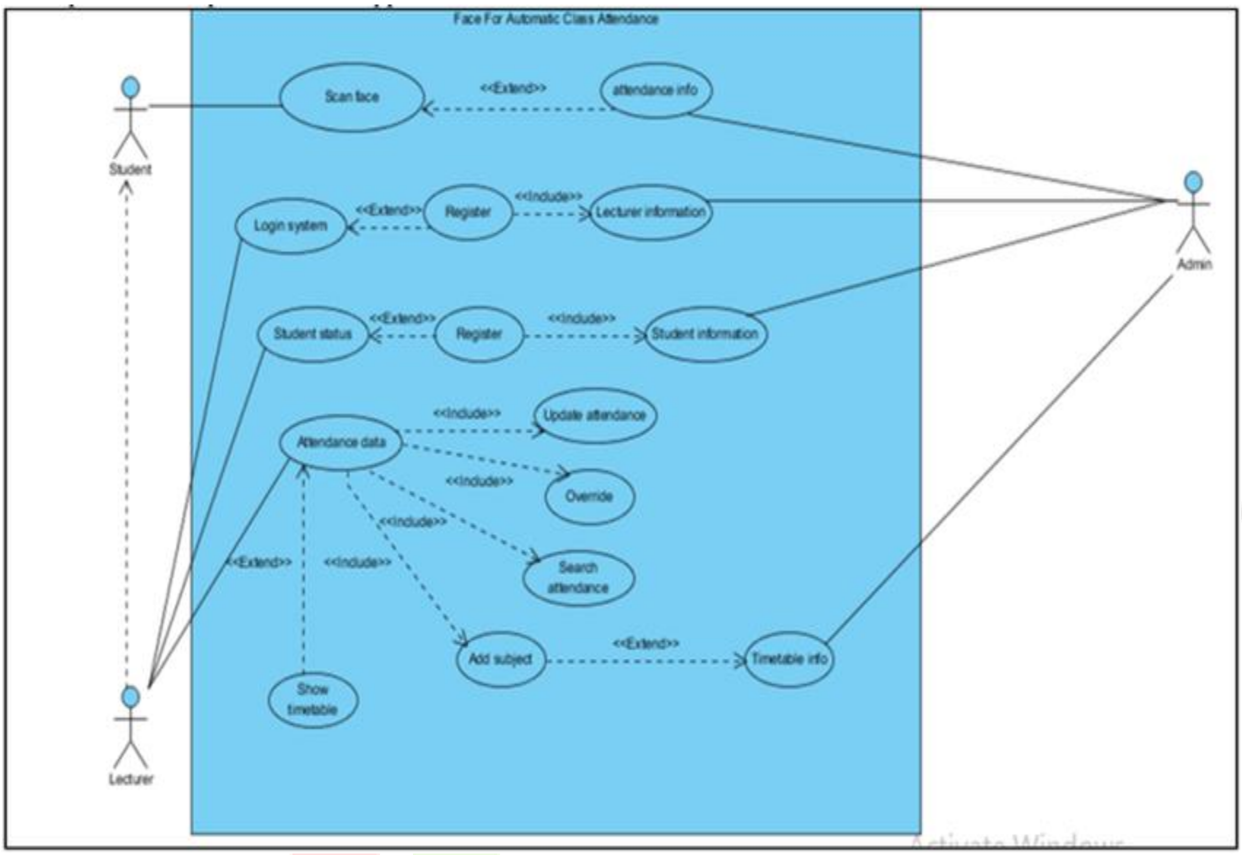

Figure 5. Use Case Diagram of the ML-Based BMI Detection System using Facial Recognition

5.2 Class Diagram:

- Class diagrams depict the static architecture of the system
- They depict the classes, their attributes, methods, and the relationships between the classes.
- Class diagrams show the organization of the system's classes and how they interact with each other.

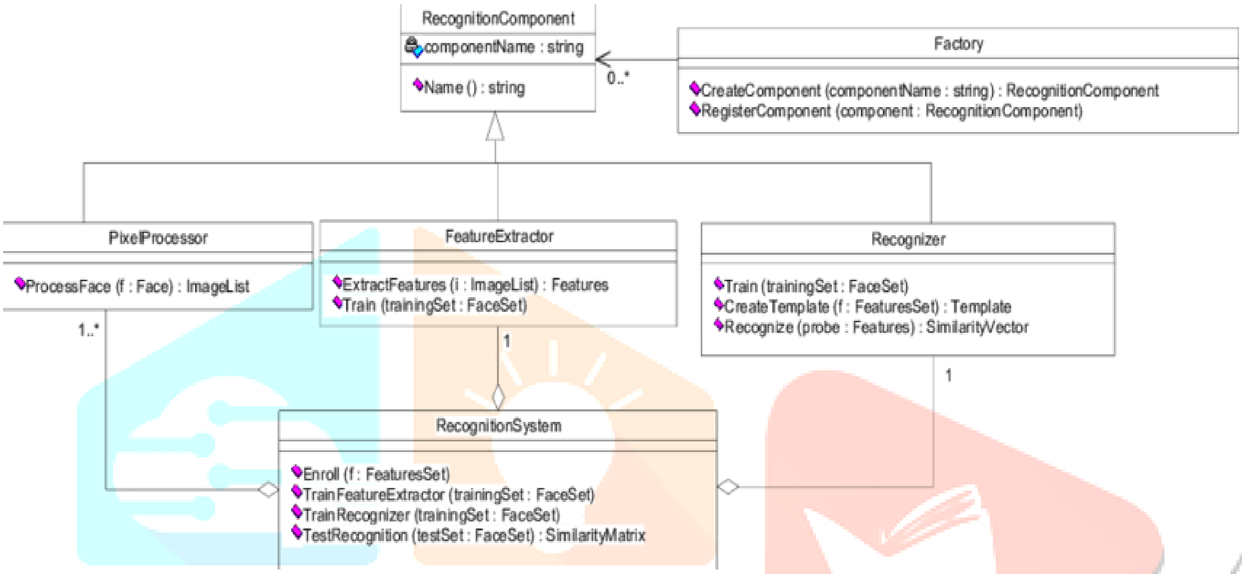

Figure 6. Class Diagram of the ML-Based BMI Detection System using Facial Recognition

5.3 Sequence Diagram:

- Sequence diagrams depict the dynamic behaviour of the system, particularly the interaction between objects or components over time.
- They illustrate the sequence of messages exchanged between objects and the order of their execution.
- Sequence diagrams help visualize the flow of control and data during a specific scenario or use case.

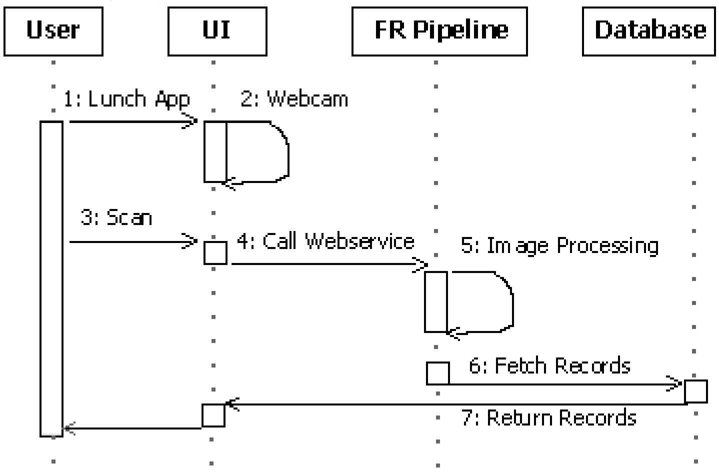

Figure 7. Sequence Diagram of the ML-Based BMI Detection System using Facial Recognition

VI. RESULTS

6.1 Screen shots

	id	UID	name	height	weight	BMI
0	1	akshay	akshay kumar	1.78	80	25.249337
1	2	ja	john abraham	1.82	94	28.378215
2	3	varun	varun dhawan	1.68	78	27.636054
3	4	tiger	Tiger shroff	1.75	72	23.510204
4	5	salman	Salman khan	1.74	75	24.772097
5	6	srk	Shahrukh khan	1.73	75	25.059307
6	7	ayushman	ayushman khurana	1.68	72	25.510204
7	8	vikky	vicky kaushal	1.83	80	23.888441
8	9	rajkumar	rajkumar rao	1.70	72	24.913495
9	10	nawaz	nawazuddin	1.68	60	21.258503
10	11	manoj	manoj bajpayee	1.75	68	22.204082
11	12	anurag	Anurag kashyap	1.78	84	26.511804
12	13	pankaj	Pankaj Tripati	1.75	70	22.857143
13	14	kirron	kirron kher	1.65	68	24.977043
14	15	richa	richa chadhha	1.65	57	20.936639
15	16	kalki	kalki koechin	1.70	53	18.339100
16	17	radhika	Radhika apte	1.60	55	21.484375

Figure 8. Dataset for ML-Based BMI Detection System using Facial Recognition.

```
data_df
```

	UID	path	id	name	height	weight	BMI
0	akshay	/home/abhay/Downloads/height_weight/akshay1.jpeg	1	akshay kumar	1.78	80	25.249337
1	akshay	/home/abhay/Downloads/height_weight/akshay10.jpg	1	akshay kumar	1.78	80	25.249337
2	akshay	/home/abhay/Downloads/height_weight/akshay11.jpg	1	akshay kumar	1.78	80	25.249337
3	akshay	/home/abhay/Downloads/height_weight/akshay12.jpg	1	akshay kumar	1.78	80	25.249337
4	akshay	/home/abhay/Downloads/height_weight/akshay13.jpg	1	akshay kumar	1.78	80	25.249337
5	akshay	/home/abhay/Downloads/height_weight/akshay14.jpg	1	akshay kumar	1.78	80	25.249337
6	akshay	/home/abhay/Downloads/height_weight/akshay15.jpg	1	akshay kumar	1.78	80	25.249337
7	akshay	/home/abhay/Downloads/height_weight/akshay16.jpg	1	akshay kumar	1.78	80	25.249337
8	akshay	/home/abhay/Downloads/height_weight/akshay17.jpg	1	akshay kumar	1.78	80	25.249337
9	akshay	/home/abhay/Downloads/height_weight/akshay18.jpg	1	akshay kumar	1.78	80	25.249337
10	akshay	/home/abhay/Downloads/height_weight/akshay19.jpg	1	akshay kumar	1.78	80	25.249337
11	akshay	/home/abhay/Downloads/height_weight/akshay2.jpeg	1	akshay kumar	1.78	80	25.249337
12	akshay	/home/abhay/Downloads/height_weight/akshay20.jpg	1	akshay kumar	1.78	80	25.249337
13	akshay	/home/abhay/Downloads/height_weight/akshay3.jpg	1	akshay kumar	1.78	80	25.249337
14	akshay	/home/abhay/Downloads/height_weight/akshay4.jpg	1	akshay kumar	1.78	80	25.249337

Figure 9. Dataset for ML-Based BMI Detection System using Facial Recognition.

```
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
[CV]  min_samples_leaf=2, bootstrap=False, n_estimators=120, min_samples_split=10, max_features=sqrt, max_depth=82, total=   0.5s
[CV] min_samples_leaf=2, bootstrap=False, n_estimators=120, min_samples_split=10, max_features=sqrt, max_depth=82
[CV]  min_samples_leaf=2, bootstrap=False, n_estimators=120, min_samples_split=10, max_features=sqrt, max_depth=82, total=   0.5s
[CV] min_samples_leaf=2, bootstrap=False, n_estimators=120, min_samples_split=10, max_features=sqrt, max_depth=82
[CV]  min_samples_leaf=2, bootstrap=False, n_estimators=120, min_samples_split=10, max_features=sqrt, max_depth=82, total=   0.5s
[CV] min_samples_leaf=1, bootstrap=True, n_estimators=780, min_samples_split=10, max_features=sqrt, max_depth=None
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[CV]  min_samples_leaf=1, bootstrap=True, n_estimators=780, min_samples_split=5, max_features=auto, max_depth=82, total=   7.9s
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[CV]  min_samples_leaf=1, bootstrap=True, n_estimators=780, min_samples_split=10, max_features=sqrt, max_depth=None, total=   2.
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[CV]  min_samples_leaf=1, bootstrap=True, n_estimators=1000, min_samples_split=5, max_features=sqrt, max_depth=91, total=   3.9s
[CV] min_samples_leaf=2, bootstrap=True, n_estimators=450, min_samples_split=5, max_features=sqrt, max_depth=10
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[CV] min_samples_leaf=4, bootstrap=True, n_estimators=10, min_samples_split=5, max_features=auto, max_depth=73
[CV]  min_samples_leaf=4, bootstrap=True, n_estimators=10, min_samples_split=5, max_features=auto, max_depth=73, total=   0.1s
```

Figure 10. CV Dataset- for ML-Based BMI Detection System using Facial Recognition.

```
report_goodness(rf_BMI_model,X_test,y_BMI_test)

Mean squared error: 0.00
Variance score: 0.87
Model Performance
Average Error: 0.0272 degrees.
Accuracy = 99.13%.
```

Figure 11. Output for ML-Based BMI Detection System using Facial Recognition.

Kernel Ridge

Height

```
model_height = KernelRidge(kernel='rbf', gamma=0.21,alpha=0.0017)
```

```
model_height = model_height.fit(X_train,np.log(y_height_train))

report_goodness(model_height,X_test,y_height_test)

Mean squared error: 0.00
Variance score: 0.80
Model Performance
Average Error: 0.0132 degrees.
Accuracy = 97.52%.
```

Figure 12. Accuracy for ML-Based BMI Detection System using Facial Recognition.

Weight

```
model_weight = KernelRidge(kernel='rbf', gamma=0.21,alpha=0.0017)
```

```
model_weight = model_weight.fit(X_train,np.log(y_weight_train))

report_goodness(model_weight,X_test,y_weight_test)
```

```
Mean squared error: 0.00
Variance score: 0.86
Model Performance
Average Error: 0.0458 degrees.
Accuracy = 98.92%.
```

Figure 13. Accuracy ML-Based BMI Detection System using Facial Recognition.

BMI

```
model_BMI = KernelRidge(kernel='rbf', gamma=0.21,alpha=0.0017)
```

```
model_BMI = model_BMI.fit(X_train,np.log(y_BMI_train))

report_goodness(model_BMI,X_test,y_BMI_test)
```

```
Mean squared error: 0.00
Variance score: 0.88
Model Performance
Average Error: 0.0311 degrees.
Accuracy = 99.01%.
```

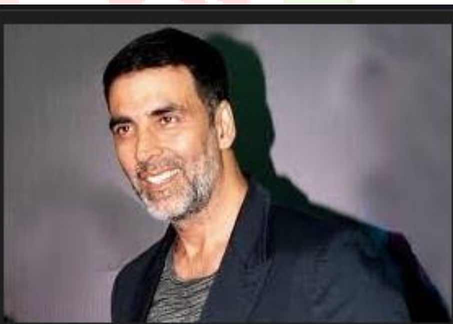
Figure 14. BMI ML-Based BMI Detection System using Facial Recognition.

prediction on test images

```
from IPython.display import Image
```

```
test_image = 'height_weight_test/vikky1.jpg'
Image(test_image)
```

Figure 15. Test Image on ML-Based BMI Detection System using Facial Recognition.



```
predict_height_width_BMI(test_image,height_model,weight_model,bmi_model)
```

```
height_weight_test/akshay1.jpg

{'bmi': 24.877827583519565,
 'height': 1.7759562913263922,
 'weight': 78.48532448422687}
```

Figure 16. Test Image on ML-Based BMI Detection System using Facial Recognition.

Figure 17. Test Image on ML-Based BMI Detection System using Facial Recognition.

VII. CONCLUSION

Body mass index (BMI) indicators and sex, smoking habit, blood pressure, waist circumference, waist-to-hip ratio (WHR), and biological health indicators such as total cholesterol (TC), HDL cholesterol (HDL-3). C), and triglycerides (TG), and the Framingham Risk Score (FRS) algorithm, underscore the importance of important cardiovascular risk markers in the early stages of cardiovascular disease This reiterates the importance of BMI in key pathways a through prevention targeting young adults, helping to identify at-risk individuals.

The system uses data mining techniques to generate BMI values, using facial characteristics related to BMI to highlight human emotions and ensure visual This BMI prediction system uses facial facial images with Harr Cascade factors a discovery algorithm and BMI learned by models generated by TensorFlow and Keras modules use use calculations, including CNN algorithm The analysis analyzes data to identify facial characteristics related to BMI and ensure that human judgment and analysis is understood is consistent. Additionally, it classifies individuals based on BMI values: underweight (BMI < 18), healthy (BMI 18.1 - 30), overweight (BMI 30.1 - 40), and obese obesity (BMI > 40).

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