Facial Recognition and Classification of Drunk Using Facial Diagrams

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ABSTRACT

The purpose of this study is to advance a system that can spot the person, which stipulates that the person is drunk using only the information pulled out from the hot-faced images. The proposed system is divided into two phases, facial recognition and segmentation. In the facial recognition phase, experimental images are visualized using dynamic face recognition algorithms: Weber local descriptor (WLD) and binary location pattern (LBP). The classification uses Fisher's exact discrimination to reduce the size of the features, and those features are classified using a classification based on a Gaussian integration model, to create an independent separation space, develop the state-of-the-art conviction "DrunkSpace Classifier." The program was vindicated using a updated database of intoxicated independents, explicitly designed for this task. Key results indicate that the performance of facial recognition phase was 100% for both types of algorithms, while the delayed detection showed an efficiency of 86.96%, which is a very committing result considering 46 independents of the database which we've created compared to others that can be found in the literature.

Keywords: Thermal Faces Images, Weber Local Descriptor, Principal Component Analysis, Linear Discriminant Analysis, Gaussian Mixture Model.

1. INTRODUCTION

Thermoregulation is the process by which the organism adjusts the internal warming within certain limits and is regulated by the hypothalamus. In humans, the temperature reached normal is about 36.7 ° (in) and 33.5 ° (in skin). In the case that the internal temperature is above 36.7 °, thermoregulation produces two processes of heat loss, sweating and vasodilation. When the temperature is below 36.7 °, the thermoregulatory system produces processes of thermogenesis (vasoconstriction and piloerection) to increase the temperature.

Other studies have shown that the thermoregulatory system can be altered depending on the mood or consumption of certain foods [1]. In a series of published papers, it is concluded that alcohol alters the functioning of the proper system by thermoregulation [2, 3], which causes vasodilation that is absorbed into the skin, which increases heat loss through convection, leading to a decrease in the body's temperature. is straight related to the amount of alcohol consumed.

Identification of intoxicated independents has its basis in biology, medicine, and anointing. Alcohol causes motor disturbances and disorders in the psychic system, leading to abnormal behaviour at the biological level, such as dilated blood vessels [2-6] and increased blood pressure. In the case of the human face, temperature increases in capillary capacity, such as around the nose, forehead and eyes.

Aside from the large number of applications in machine learning, such as facial recognition, facial recognition, and human identification, the computer programs used for the classification of intoxicated independents are not widely studied. The most notable work has been done by these researchers at the University of Patras, Greece [7-11], who have tried to classify a person who is bored or drunk based on their facial differences. In simple terms, in [7, 10] and [11], it is shown that the frontal region and the nose are a good fit for identifying information to classify people as late or difficult, using the neural network to perform the classification task. In [9], it is argued that alcohol causes an increase in eye temperature, which may be useful for differentiation. In [8], extraction from the vascular network was proposed based on the works of Buddharaju et al. [3-6]. When we analysed the total area in pixels of the artery network of a sensitive subject compared with the drunk subject, it was possible to find an index (factor) to determine whether the study had consumed alcohol. In [10], the aim is to show the possibility of distinguishing between sad and drunk people using the size of pixels found in specific regions or areas of the face (forehead, nose, and mouth). The space for distinguished features can be created using this energy; however, this study used only a small number of studies (8 people) and people experienced certain symptoms (weight and same height), and as a result, it is not possible to confirm the normal classification.

Also, in [10], a method is proposed for detecting regions with high facial flexibility by comparing a person's intensity while intoxicated and in a state of intoxication. It is come to an end that the region on the forehead indicates an increase in temperature relative to the nose region. The feature extraction used in [10] is based primarily on examining multiple pixels around the smooth surface areas, where methods are used to reduce the dimensionality of features, comparatively Linear Discriminant Analysis (LDA) or else principal component analysis (PCA). The space produced by the LDA, called "DrunkSpace," is used to differentiate between drunk and drunken states.

In this case, the purpose of this study is to generate a classification scheme, based on "DrunkSpace" proposed in [10], to identify whether a person is intoxicated, using computer vision and pattern recognition methods. The main purpose is to extract the features (patterns) of the thermal imagery obtained from a drunk to construct a Bayesian classifier based on a Gaussian mixing model (GMM) [12, 13]. The superiority of thermal imaging is that it can be used to find patterns based on thermal information of the face, which is connected to the thermoregulation processes of the human face and the content of alcohol consumed. Alternatively, since there is a large amount of data available that has a reduced number of hot pictures of drunk people, it is proposed to create a public drinking database to study the classing of an intoxicated person (available at https://goo.gl/7Gxs18).

2. THERMAL FACE DATABSE

This part gives us documentation in particular how the Pontificia Univer-sidad Católica de Valparaíso-Drunk Thermal Face database (PUCV-DTF) is created.

A. Recruitment

A call was made on the opening of the specialists at the Electrical Engineering school at Pontifica Universidad Católica de Valparaíso. People who attended this call were informed of the research legislation and signed an informed consent form previously approved by the university's Ethics Committee.

B. Participants

A total of 46 people were selected, 40 men and 6 women. Median age was 24 years of standard deviation of approximately 3 years (minimum age was 18 years, and average age was 29 years), in good health with no alcohol-related problems. This analysis was performed using a screening test designed to exclude people who regularly drink alcohol.

C. Process

Attendees arrived at the robotics lab where they rested for 30 minutes to strengthen the metabolism in the laboratory temperatures. The subject then consumed a 355 m bean of 5.5 ° beer, waited another 30 minutes in the laboratory, and repeated the process until four beers were consumed. See Table 1 for the entire capture process.

Table 1: Plan of action of gathering the PUCV-DTF database.

Stage	Description	Time
Rest 1	Advent at the laboratory and data asset (mass, zenith, etc.)	30 min
Meas. 1	Advent at the laboratory and data asset (mass, zenith, etc.) Body heat and alcoholic measurement in body	1 min
Capt. 1	50 pictures of the subject (sober) are represented	1 min
Cons. 1	A can of beer is drunken	5 min
Rest 2	Balancing of growth in the laboratory	30 min
Meas. 2	Body heat and breath test computation	1 min
Capt. 2	50 photos of the subject (1 beer) are represented	1 min
Cons. 2	A can of beer is drunken	5 min
Rest 3	Balancing of growth in the laboratory	30 min
Meas. 3	Body heat and breath test computation	1 min
Capt. 3	50 pictures of the subject (sober) are represented	1 min
Cons. 3	A can of beer is drunken	5 min
Rest 4	Balancing of growth in the laboratory	30 min
Meas. 4	Body heat and breath test computation	1 min
Capt. 4	50 pictures of the subject (sober) are represented	1 min
Cons. 4	A can of beer is drunken	5 min
Rest 5	Balancing of growth in the laboratory	30 min
Meas. 5	Body heat and breath test computation	1 min

Ending	50 pictures of the subject (sober) are represented	1 min

Upon completion of the procedure, subjects with concentrations of 0.8 g / L of blood alcohol (intoxicated) should remain in their place until the percentage of alcohol dropped to less than 0.2 g / L. This was confirmed by quantitative tests. It should be noted that during the whole trial the paramedic was in a laboratory for the assessment of human condition.

D. Thermal Imaging

The thermal camera used was a FLIR TAU 2 [14] with a resolution of 640 x 480 pixels, a frame rate of 30 frames per second, a temperature sensitivity of 50 mK, and a spectrum scope between 7.5 and 13.5 µm. Data includes 46 independents with five subsets, a total of 250 images per subject and 50 images per item. The set is divided into five subtitles: “Sober,” “Beers 1,” “Beers 2,” “Beers 3,” and “Beers 4,” corresponding to the data capture process, as summarized in Table 1. Following the assumption of thermal assumptions, prerocessing, where all images were generated and aligned with optical coordinates, which were manually tagged, provide a final resolution of 81 x 150 pixels. The thermal images were customized using (1), which included using a precise map to pixel intensity values in the range [$N_{\min}$, $N_{\max}$]:

$$I_{\text{norm}}(i,j) = \frac{I_{(i,j)} - I_{\min}}{I_{\max} - I_{\min}} (N_{\max} - N_{\min}) + N_{\min}, \quad \forall (i,j) \in \Omega, \tag{1}$$

where $I_{\min}$ and $I_{\max}$ have smaller and higher values in the image: $I_{\min} = \min_{(i,j) \in \Omega} I_{(i,j)}$, and $I_{\max} = \max_{(i,j) \in \Omega} I_{(i,j)}$. For experiments, a value of [0,255] is used. An example of a topic with 5 subsets is shown in Figure 1. In order to highlight the information available on alcohol, color was applied to images from subsets. The figure also shows forehead temperatures (FT), nose temperatures (NT), and alcohol test (AT) measures. For parents, the prescribed values of FT, NT, and AT for each subject are shown. Please note that the temperature of the hot face image varies due to alcohol. However, the nose difference varies when the subject is finished with beer. This effect may be caused by the process of thermoregulation or the respiratory effect produced during the respiratory or respiratory phase or a combination of both.

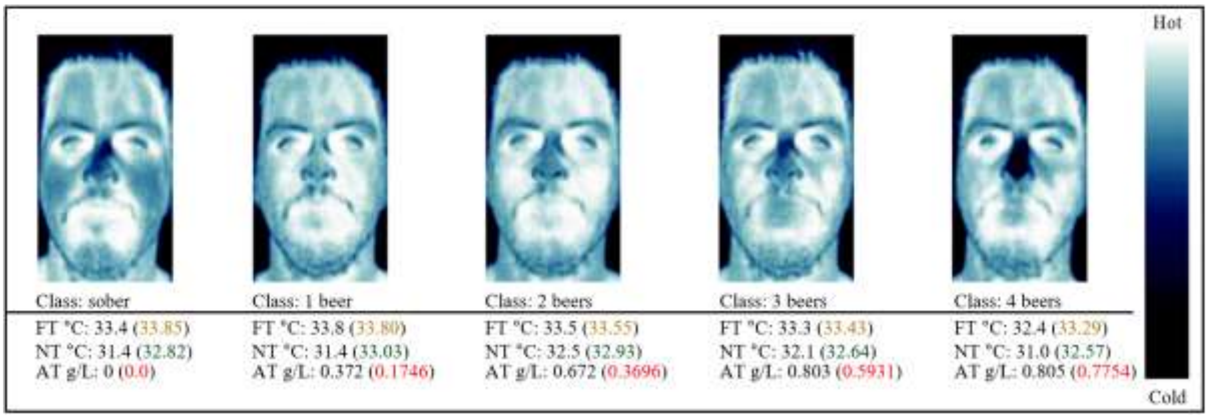

Figure 1: Pictures in pseudo colour to demonstrates how the face becoming different after consuming 4 beers.

Depending on the involvement of alcohol found in each breath test measure, the price range for each class can be viewed in Table 2. Note that available alcohol levels indicate that classes are passing due to variations in the subjects taken (different weight, height, age, sex, etc.). However, in our research, we wanted to distinguish whether a study made sense or used beer (1 Beer, 2 Beers, 3 Beers, or 4 Beers), regardless of the amount of alcohol a person has. See in detail the temperature and alcohol concentrations in the document attached to the data link.

Table 2: Range of alcohol concentration by classes.

Class	Minimum (g/L)	Maximum (g/L)	Mean (g/L)
Sober	0	0	0
1 Beer	0	0.39	0.17
2 Beers	0.15	0.68	0.37
3 Beers	0.29	1.29	0.59
4 Beers	0.43	1.68	0.78

3. FEATURE EXTRACTION AND CLASSIFICATION

The feature extraction process consists of selecting local regions of the hot face image and extracting the information using dimension reduction techniques. As mentioned above, the process developed in this study is related to the generation of "DrunkSpace," as outlined [10]. In [10], data from different regions of the face are extracted from a 20-point grid. The problem with the grid proposed in [10] is that there is no geographical information in the element points. For this reason and inspired [15], a separate grid of 22 points was selected. In [15], the aim is to produce a thermographic map of the human face, where multiple sensors are located on the face and neck of each subject. These 22 points are selected for positions where the capillaries and arteries cross the face, as can be seen in any sample of faces shown in Figure 2. Once the grid has been defined, details are extracted from the thermal face images. Since the details in the selected grid pixel may be masked by noise, we decided to look at the neighbourhood of 3 × 3 pixels around each point of the grid and calculate the average size of each of the 22 faces. As the images in the database were aligned, the grid was used for all database studies as a separate mask.

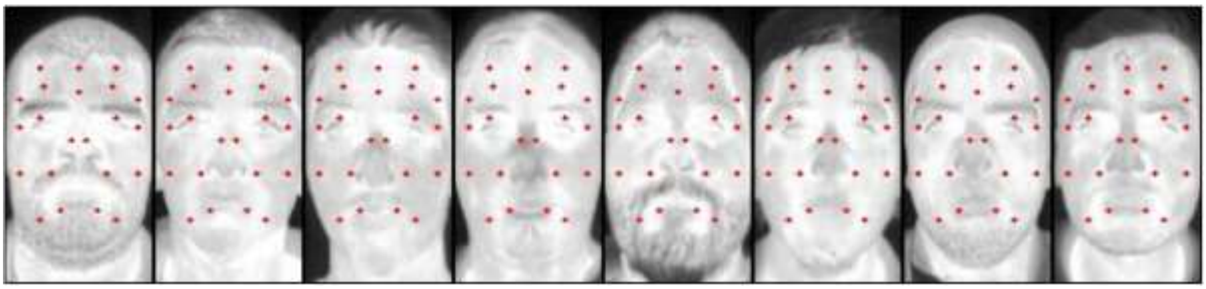

Figure 2: Characteristic obtaining of regions used for subjects in the database.

After extracting the features of each thermal image, a 22-meter display was produced. Therefore, for a particular topic, there are 50 categories for each category ("Sober," "Beer 1," "Beers 2," "Beers 3," and "Beers 4"). It is not recommended to use a 22-segment vector to be categorized because of its small size, the difficulty of producing a hyperplane that separates all of these components, and the high computational cost it can include. Therefore, to reduce the size, the Fisher linear regression model is used.

A. Fisher Linear Discriminant Analysis (FLD)

First, it is assumed that there is a separation problem involving two different classes (W_1 and W_2), and in each phase, there are n_i samples of a magnitude. So, there is a set of n samples: $x = \{x^1, x^2, x^3,., x^n\}$, n_1 corresponding to the class W_1 and n_2 to W_2, and so on. The FLD method aims to find the transition from the x-space to the y-space, by using the exact guesses of all samples (x) in a row, using weights w. However, the selected line should increase the separation of the estimated samples between the different classes. The exact combination that allows us to point the samples from the x-space to the y-space is represented in

$$y = w^t x, \tag{2}$$

where

$$\mathbf{w} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}. \tag{3}$$

To obtain an adequate line of guessing, we must define the average of the differences between the data entered to maximize this difference. The solution proposed by Fisher [16] is to maximize the function that represents the difference between the price levels of each class, which is determined by the degree of variance that exists in each class. The function of the J (w) expansion function can be represented as a function of two scatter metrics, S_W and S_B as shown

$$J(\mathbf{w}) = \frac{\mathbf{w}^t \mathbf{S}_B \mathbf{w}}{\mathbf{w}^t \mathbf{S}_W \mathbf{w}}. \tag{4}$$

S_W (matrix dispersed within layers) can be represented as a function of initial samples (x-space) or as a function of fuzzy samples. S_B (a matrix that is dispersed between classes) can be defined based on original and predictive samples. Both definitions are shown below along with the covariance matrix definition. See (5), (6), and (7) for the streaming matrices.

$$\mathbf{S}_i = \sum_{x \in w_i} (\mathbf{x} - \mu_i)(\mathbf{x} - \mu_i)^t, \tag{5}$$

$$\mathbf{S_w = S_1 + S_2,} \tag{6}$$

$$\mathbf{S_B = (\mu_1 - \mu_2)\,(\mu_1 - \mu_2)^t,} \tag{7}$$

where μi is the value of the number of first class samples and w is the weight of the sample. Finally, correct guesses are obtained using instruments w^* (8):

$$\mathbf{w}^* = \arg\max_w \left(\frac{\mathbf{w}^t \mathbf{S}_B \mathbf{w}}{\mathbf{w}^t \mathbf{S}_W \mathbf{w}} \right) = \mathbf{S}_W^{-1} (\mu_1 - \mu_2). \tag{8}$$

This optimal solution w^* is given by the eigenvector (s) of $\mathbf{S_X = S_W^{-1}(\mu_1\text{-}\mu_2)}$, which corresponds to the maximum eigenvalue. Applying the FLD to our problem reduced the arteries to 22 sizes, while also increasing the distance between the methods of the different classes and reducing the variability of each class. This can be found in the following example in Figure 3. Figure 3 (a) shows the plane in which two randomly selected features are found in a given subject. From this figure, it is clear that not all classes are distinguished, since many features are common between classes. However, when using the FLD method, the detected DrunkSpace (see Figure 3 (b)) is fully separated and it is viable to identify the predicted phases of each phase.

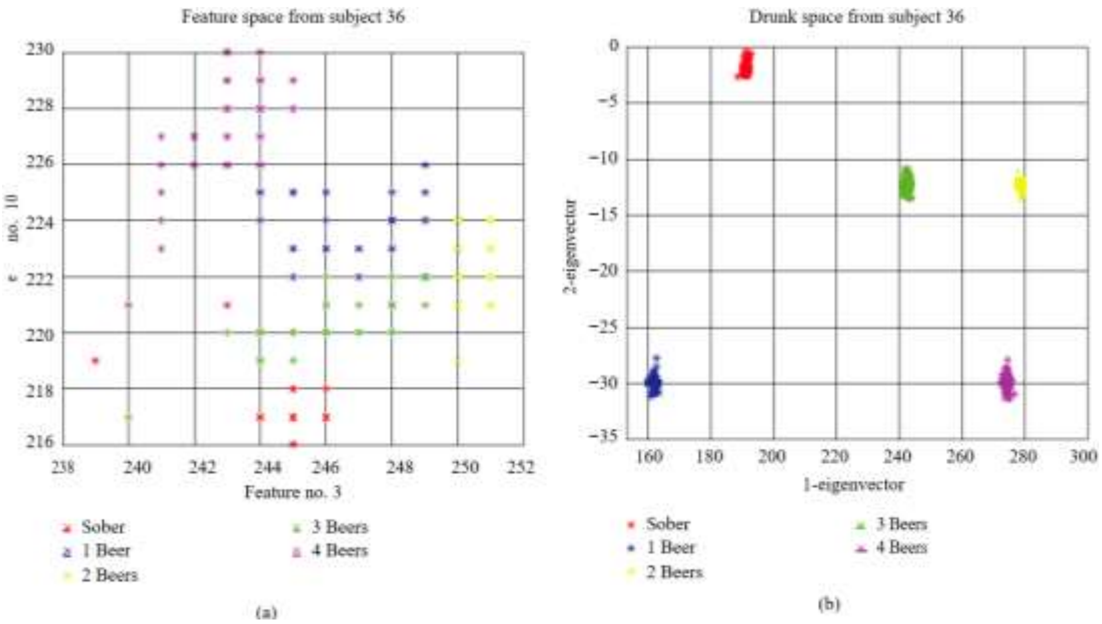

Figure 3: (a) Sample of a feature space of two characteristics entropically selected for a subject. (b)DrunkSpace acquired through FLD for the identical subject. The DrunkSpace acquired is completely distinct for these two characteristics.

B. Gaussian Mixture Model (GMM)

Once the dimension (FLD) was reduced, the Gaussian mixture model (GMM) was chosen to perform the classification. GMM is a dynamic distribution with respect to the density function which is a linear combination of a finite number of Gaussian distributions. Each complete Gaussian distribution represents a different category. In this scenario, four were distributed as training classes (Sober, 1 Beer, 2 Beers, and 3 Beers) to produce GMM. The remaining distribution (4 Beers) was used as the test set. The analysis of the test data was done by analyzing the probability that the data were for each GMM distribution. Finally, the training information is given to the distribution (class) that may belong to it.

The idea of how this approach is based is briefly described below. Let Y be a D-dimensional non-linear integral with a random variable with a nonlinear function (pdf) written as a linear combination of the original pdfs (see (8)). If the stream that compiles this mixture is Gaussian, then the pdf is known as the Gaussian mixture.

$$p\frac{y}{\theta} = \sum_{i=1}^{I} a_i N\left(y \mid C = i, \beta_i\right), \tag{9}$$

where I represent the mass of the first element (C) of the mixture and θ represents the set of parameters, which is where the set of parameters $\theta = \{\alpha_1, \ldots, \alpha_I, \beta_1, \ldots, \beta_I\}$ associated with each distribution comprises the combination with $\alpha = \{\alpha 1, \ldots, \alpha I\}$ is the weight for each distribution of the mixture. Gaussian quantities are components of a complex, and the mean and covariance $\beta i = \{\mu_i,, \sum_i\}$ of frames are represented using

$$N\left(y \mid C = i, \beta_i\right) = \frac{1}{2\pi^{D/2}\left|\Sigma_i\right|^{1/2}} \cdot \exp\left(-\frac{1}{2}\left(y-\mu_i\right)^t \sum_i^{-1}\left(y-\mu_i\right)\right). \tag{10}$$

The solution to the separation problem is described below. First, consider a set of samples $y = \{y_1, \ldots, y_j\}$ in which the yj ∈ RD is one of the independent effects of the Y random variable; then, the probability of y is defined by the following cognitive function (in independent recognition and the like) given by (11).

$$L(\theta) = \prod_{j=1}^{J} p\left(y_j \mid \theta\right). \tag{11}$$

Now, the probability of y should be increased. Using some algebraic transformations (see [17]), it is possible to represent the probability function as a function of the objective function, used in the Gaussian Mixture Model (12):

$$\theta^* = \arg\max_\theta \sum_{j=1}^{J} \log \left\{ \sum_{i=1}^{I} a_i N(y \mid C = i, \beta_i) \right\}. \quad (12)$$

This is a complex installation problem that is usually solved using the standby (EM) algorithm [18]. More details on Gaussian mixture models are available in [12, 13]. In the present study, the GMM technique is used in Matlab R2015a and an EM algorithm was chosen to do exactly that. Each Gaussian distribution (of combinations) is defined by sets of established samples (designated samples) of different training categories ("Sober," "Beer 1," "Beers 2," and "Beers 3", and the experimental data, which we want to classify, are class samples "The 4 Beers."

Figure 4 shows an example of a GMM partner for the same lesson used in Figure 3. This figure shows the DrunkSpace section made with information from the training sections: "Sober," "Beer," "2 Beers," and "3 Beers Beer. "The circuits are able to be seen in Figure 4 are provoked using DrunkSpace prophecies from Fisher in the GMM classroom for the study sections; therefore, one DrunkSpace class is provoked. Note that the regions found indicate that you may have been in one of the courses: "Sober," "1 Beer," "2 Beers" and "Beers 3." The setup "4 Beers" is used to confirm the partition. Figure 4 shows the experimental set ("4 Beers") magenta, which is separated primarily by the region in the section "3 Beers." Points scored for this example are 0% for the "Sober" category, 0% for the "1 Beers" category, 16% for the "2 Beers" category, and 84% for the "3 Beers" category.

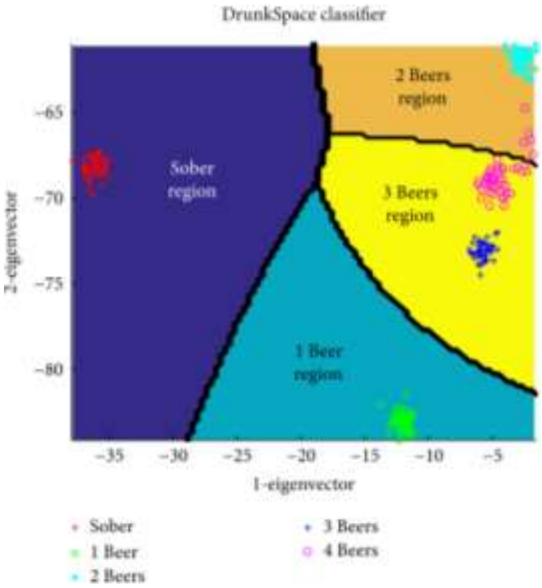

Figure 4: Sample of a DrunkSpace arrangement from subject 36. The circles act for the test sub group "4 Beers." The prospect obtained for this sample are 0% for the "Sober" category, 0% for the "1 Beer" category, 16% for the "2 Beers" category, and 84% for the "3 Beers" category, showing a high prospect of identifying the subject as being in a drunk state.

4. EXPERIMENT AND EVALUATION OF THE PROPOSED SYSTEM

The recommendation for this study consists of two phases: facial recognition and targeting of an intoxicated person. In Figure 5, a general outline of the proposed scheme is shown. The first phase determines who the people are for further stage analysis. Once the surface of the subjects has been adopted in the first phase, the second phase is responsible for generating the flipping feature with the FLD and the alcohol separation is performed with the GMM classifier. The description of each step is illustrated in detail below. The data used in the research is the PUCV-DTF, described in section 3.

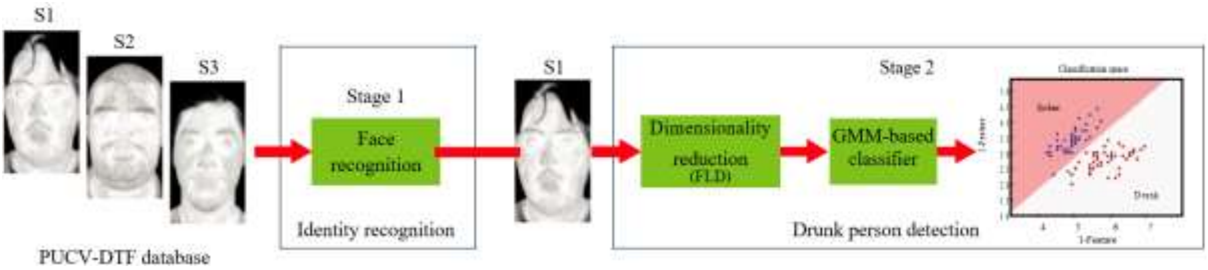

Figure 5: Proposed system outline.

A. Stage 1

Facial recognition is an important part of a complete alcohol screening program because it determines the identity of the people in the database. The facial recognition system used in this study was analyzed using two current most widely used definitions in the literature: the LBP descriptor [19] and the WLD definition [20]. Both methods use distance histogram distance (HI) as a measure of variance.

The experiment involved using images from PUCV-DTF data to generate a gallery set and a test set. The gallery set is made up of face images of low-key subjects, while the test set is combined with images of subjects after drinking beer ("1 Beer," "Beers 2," "Beers 3," and "4 Beer"). The results obtained by the recognition program are shown in Table 3. As can be seen in Table 3, both definitions used obtain a 100% yield on the recognition rates of each test set, due to the absence of temporal variations in the data images, because they were acquired over three hours. However, the performance of the facial recognition system can be reduced if the images are acquired at a very high time [21–23].

Table 3: Identifying rates come by WLD and LBP methods through pictures from the PUCV-DTF database.

Method	Recognition rate [%]
WLD-HI	100.0
LBP-HI	100.0

B. Stage 2

Once the identity of the subject has been approved, we go to the State Identification section drunk. In order to perform this function, the second phase is divided into two phases: feature extraction and characterization. Feature includes a selection of relevant information from the face, which is used to determine whether the person is stubborn or drunk. Replacement is placed in the split registry section (called DrunkSpace), where the items will be extracted, and depending on this assumption, classification of the title will be performed.

As mentioned in Section 3, feature extraction is performed using a 22-point grid. The FLD method is then used to reduce the size of the data by adding feature packets from size 22 to size 2. Split space (DrunkSpace) was generated in each study based on the method of the Gaussian mixing model (see section 3). Each DrakSpace is created using MATLAB R2015a. The training data used are those for the consideration of feature resources from the class images of the fun topic and subject after drinking 1, 2 and 3 beers. Study pictures after drinking 4 beers were used as a test set.

The experiment to perform this installation was performed as follows: an experimental feature display, corresponding to the set "4 Beers," is displayed on DrunkSpace. This project was carried out using the same autovectors used to make DrunkSpace (FLD) for each subject (using the training sets "Sober," "1 Beer," "2

Beers," and "Beers 3"). Once the diagnostic information is received, the student entering the subject restores the information opportunities for each training class ("Sober," "Beer 1," "2 Beers," and "Beers 3"). The highest probabilities returned by the classifier indicate how the expected test data ("4 Beers") are categorized. For example, if a classmate has returned a number of test opportunities that are thought to be part of each training class of 0,1, 0,2, 0,3 and 0,4 ("Sober," "Bear 1," "2 Beers," and "3 Beers," p.), where the considered training data were considered to be a intoxicating study, with at least three beers.

Table 4: Outcomes of the categorization of drunk people through the PUCV-DTF database.

	Sober	1 Beer	2 Beers	3 Beers
Classification [%]	13.4	9.09	29.39	**48.48**

In the results shown in Table 4, it is important to note that the program achieved an identification rate of 86.96% for drunk people, when we look at the correct classification where training data were identified as 1, 2, or 3 beers. When we divide this 86.96% into the corresponding category for each "drunk" class, we see that 9.09% were placed in the "1 Beers" class and 29.39% were classified in the "2 Beers" class, and 48.48% were classified in the "3 Beers" category. Beers ". It is important to highlight the clear visual trends associated with the correct identification of 86.96%; this trend shows a steady increase in the price of the split from the class "1 Beers" to the class "The 3 Beers." This may be attributed to the fact that the test data used are related to the subjects drinking 4 cans of beer, leading to the conclusion that the factors considered in DrunkSpace follow a specific energy and travel to specific DrunkSpace regions while the subject consumes alcohol. It is because of this that approximately half of the test data ("4 Beers") are estimated in the DrunkSpace region corresponding to the highest alcohol level.

5. Conclusions

This document introduces a computer vision system that identifies people with addiction. The program is structured into two major categories, one is facial and the other is divided into drinks. The facial recognition category provides ownership of the formerly stored database, while the classification category identifies the person's status, indicating whether the subject has used alcohol. Inspired by [10], the classifier uses the Fisher linear discriminant (FLD) method to reduce the size of the element's ingredients and produce a supplement called "DrunkSpace." We then use a Bayesian classification based on Gaussian mixture models (GMM) to determine whether the material is in a state of intoxication or not.

The results obtained from this study indicate that the proposed alcohol screening program achieves an 87% success rate; that is, the system is able to identify if a person drinks at least one liter of beer. In addition, the proposed system achieves 100% recognition rates at the facial recognition stage using either the LBP method or the WLD method. It is important that the facial recognition class should be strong in a state of intoxication.

It is important to mention that the good results obtained are mainly due to the fact that the selected properties of the extracts produce the effects of metabolic changes on the surface of the subjects and are due to processes related to other environmental factors, such as thermoregulation, which cannot be detected by the thermal camera.

In the findings, we hope to encourage other researchers to research the categories of intoxicated independents, as it will lead to unsafe programs that can be of benefit to society. As a future study, we hope to increase the problem of demographic segregation, that is, produce a generic classifier that can be used to identify people in a drunken state without weight, sex, or height and not as they did in this study.

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