Effect of Illicit Drug Abuse on Face Recognition

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Abstract

Over the years, significant research has been undertaken to improve the performance of face recognition in the presence of covariates such as variations in pose, illumination, expressions, aging, and use of disguises. This paper highlights the effect of illicit drug abuse on facial features. An Illicit Drug Abuse Face (IDAF) database of 105 subjects has been created to study the performance on two commercial face recognition systems and popular face recognition algorithms. The experimental results show the decreased performance of current face recognition algorithms on drug abuse face images. This paper also proposes projective Dictionary learning based illicit Drug Abuse face Classification (DDAC) framework to effectively detect and separate faces affected by drug abuse from normal faces. This important pre-processing step stimulates researchers to develop a new class of face recognition algorithms specifically designed to improve the face recognition performance on faces affected by drug abuse. The highest classification accuracy of 88.81% is observed to detect such faces by the proposed DDAC framework on a combined database of illicit drug abuse and regular faces.

1. Introduction

Illicit drug abuse has become one of the primary health and social concerns in today's world. According to World Drug Report [18], an estimated 183,000 drug related deaths were reported in 2013. It is estimated that a total of 246 million people aged 15-64 have used illicit drugs, mainly substance belonging to cannabis, cocaine or amphetamine-type stimulants. The problem of illicit drug abuse is becoming more apparent, considering that 1 out of 10 drug users is a *problem drug user*, who is suffering from drug dependence.

There has been a lot of research in understanding the deteriorating effect of drugs on physical and mental health

Figure 1. Sample images that demonstrate the significant effect of illicit drug abuse on faces. Noticeable variations can be seen in the facial features of the *after* images of these subjects. Images taken from rehabs.com

[17]. Certain drugs when taken continuously in large quantities can cause physiological changes in the skin. For instance, long term effects of methamphetamine (meth) and heroin can cause severe weight loss and skin sores. Reece [15] noted the evidence of accelerated aging due to addiction of opiates. In 2004, a deputy at Multnomah County Sheriff's Office put together mug shots of persons booked into the detention center of Multnomah County [1]. The face images were released as "Faces of Meth" in order to make people realize the detrimental effect of substance abuse. Later, some faces belonging to heroin, crack and cocaine were added to the collection. A sample of such images are shown in Figure 1 where the accelerated aging and formations of scars are very evident.

While illicit drug abuse and its detection has applications in health and medical areas where several research directions are being explored [3], the effect of illicit drug abuse on automated face recognition systems has not been explored. There are several large scale national ID projects and biometric systems that utilize face as a modality. In these applications, such fast and unstructured facial variations caused due to illicit drug abuse are not considered. Therefore, these systems may not be able to match before-and-after images affected due to illicit drug abuse.

To the best of our knowledge, there is a lack of experimental evaluation or formal study to understand and analytically demonstrate the effect of illicit drug abuse on the current face recognition algorithms. This paper attempts to bridge this gap and showcases the impact of facial variations caused due to illicit drug abuse. We also present a dictionary learning approach to classify faces into categories: *drug abuse faces* and *regular faces*. The contributions of this paper are summarized below:

1. Creating the first Illicit Drug Abuse Face (IDAF) dataset containing before and after images of 105 subjects, collected from the internet.

2. Demonstrating the impact of facial variations caused due to illicit drug abuse on face recognition. The low performance of two commercial face recognition systems and two face descriptors on faces that have considerably changed due to consistent use of drugs.

3. Proposing a non-invasive classification algorithm using dictionary learning to detect face images affected due to illicit drug abuse such that it can be used in conjunction with current face recognition systems. The aim of such a framework is to reliably separate possible drug abuse face images where current systems may not identify the person correctly.

2. Effect of Illicit Drug Abuse on Face Recognition Algorithms

Due to the novelty of the research problem, there is no publicly available database. Therefore, we first collected a database from online resources. As part of the research efforts, we will release the database to the research community. To understand the performance of face recognition algorithms on the database, a set of state-of-the-art face recognition algorithms including two commercial systems are used.

2.1. Creation of Illicit Drug Abuse Face (IDAF) Database

Due to the sensitive nature of the process and privacy issues, it is extremely difficult to find images where people admit prolonged illicit drug abuse. However, as mentioned above, [1] shows different images of illicit drug abusers with their consent, to raise concern about the physical changes and harmful effects of drugs and their addiction. Using these images and other images collected from the internet [2], Illicit Drug Abuse Face (IDAF) dataset[1] is created. This dataset contains two frontal face images: first when the subject was not taking any kind of drug (before image) and second when there has been a substantial amount of illicit drug abuse (after image). The database contains 210 images pertaining to 105 subjects. The database comprises of face images of methamphetamine, cocaine, heroin, and crack addicts.

2.2. Face Recognition Algorithms for Evaluation

Two Commercial-Off-The-Shelf (COTS) systems, Face-VACS [5] and Luxand [12] are utilized to study the effect of illicit drug abuse on face recognition algorithms. Local Binary Patterns (LBP) [13] and Histogram of Oriented Gradients (HOG) [6] along with χ^2 distance measure are also used to study the effect of their performance on these images. These algorithms take into account the texture and the oriented gradients and are popular for the task of face recognition.

2.3. Experimental Scenarios

To evaluate the effect of illicit drug abuse on face recognition, three different experimental scenarios are constructed.

Scenario 1: The first experiment (called *Drug Faces*) is conducted using the Illicit Drug Abuse Face (IDAF) dataset that contains *before* and *after* face images of 105 subjects who are drug users.

[1]The database can be accessed at `http://iab-rubric.org/resources.html#face`.

Scenario 2: The second experiment (called *Regular Faces*) is used to obtain the baseline performance of the face recognition systems. For this purpose, two frontal images of 300 subjects from CMU-MultiPIE dataset [7] and 700 subjects from the visible spectrum of CASIA-VIS-NIR dataset [11] are chosen to form a database of regular faces.

Scenario 3: The third experiment (called *Combined Faces*) uses two frontal images of 268 random subjects from the 300 subjects of CMU-MultiPIE used for the previous experiment, and similarly 627 subjects from 700 subjects of CASIA-VIS-NIR used in the previous experiment. In addition, 105 subjects are added from the Illicit Drug Abuse Face (IDAF) dataset to make it a complete set of 1000 subjects.

To evaluate the performance of the commercial systems and existing descriptor-based face recognition algorithms, the *before* image in all the three scenarios are used as a gallery while the *after* image is used as probe.

2.4. Experimental Results

Figures 2, 3 and 4 show the Cumulative Matching Characteristic (CMC) plots pertaining to the above experiments. The key findings are reported below:

- The CMCs in Figure 2, 3 and 4 show Rank-1 accuracy for *Regular Faces*, *Combined Faces* and *Drug Faces* scenarios. Both the commercial systems perform very well on the images from the *Regular Faces* database and the results are used as baseline for comparison purposes. However, there is a noticeable drop in performance for both the systems, when images of Illicit Drug Abuse Face (IDAF) dataset are introduced in the *Combined Faces* scenario. As can be seen, the Rank-1 accuracy is 99.4% and 99% respectively for FaceVACS and Luxand for the *Regular Faces* scenario. In the *Combined Faces* scenario, this drops down to 96.6% and 94.9%.

- A similar decrease in performance is observed for both LBP and HOG descriptors as shown in Figures 3 and 4 .

- The decrease in performance can be attributed to the images from the Illicit Drug Abuse Face (IDAF) dataset. This can be seen from the *Drug Faces* scenario where both the commercial systems and facial descriptors perform badly in the recognition task. Figure 4 shows the performance of the commercial systems is 0.07% and 0.05% for FaceVACS and Luxand in the *Drug Faces* Scenario respectively. HOG performs the best with an identification accuracy of 37% Rank-1 while LBP gives 28% Rank-1 accuracy.

These experimental results clearly highlight the challenges of illicit drug abuse face images using current face recognition algorithms. With the widespread use of drugs globally and their effect on the skin texture and alteration of facial features, there is a major need for face recognition algorithms to address this challenge.

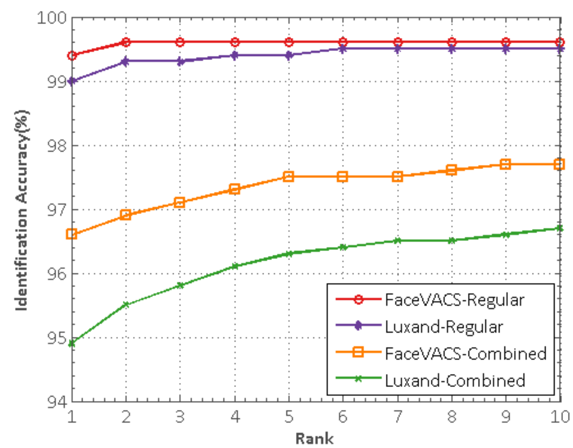

Figure 2. CMC curves for *Regular Faces* and *Combined Faces* Scenario when COTS systems FaceVACS [5] and Luxand [12] are used. It is seen that introduction of illicit drug abuse images lowers the performance of COTS.

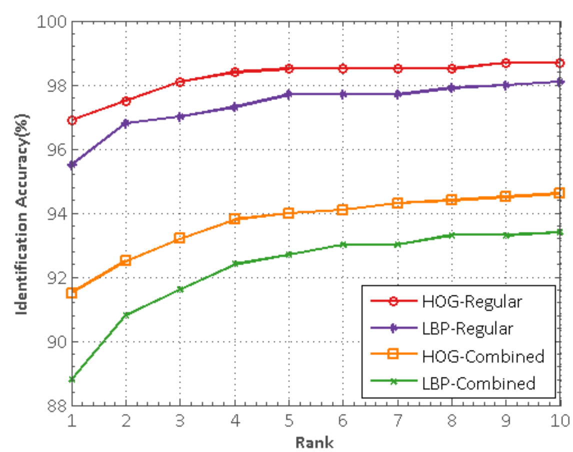

Figure 3. CMC curves for *Regular Faces* and *Combined Faces* Scenario when two face descriptors, LBP [13] and HOG [6] are used. It is seen that introduction of illicit drug abuse images lowers the performance of the face descriptors as well.

3. Proposed Dictionary Learning based Illicit Drug Abuse Face Classification Framework

The previous section demonstrates the effect of facial feature variations caused due to illicit drug abuse on cur-

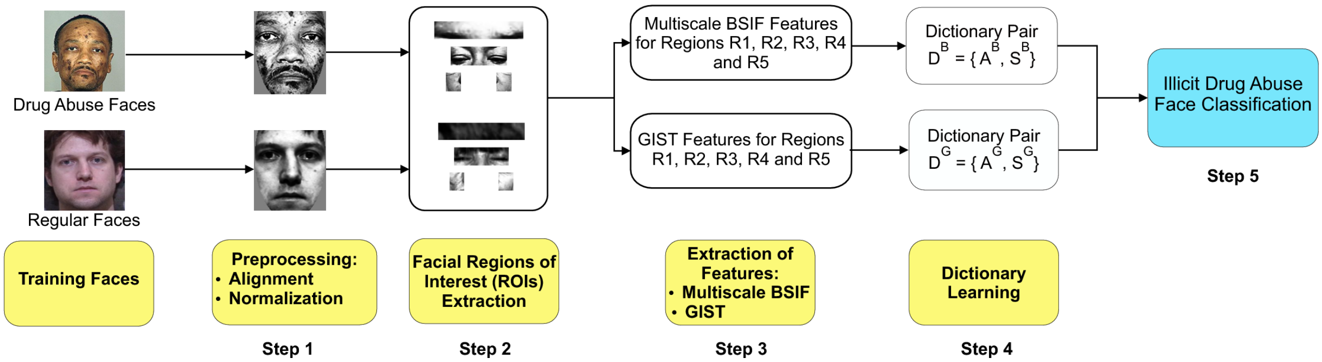

Figure 5. Proposed **D**ictionary learning based illicit **D**rug **A**buse face **C**lassification (DDAC) framework to classify faces affected by drug abuse.

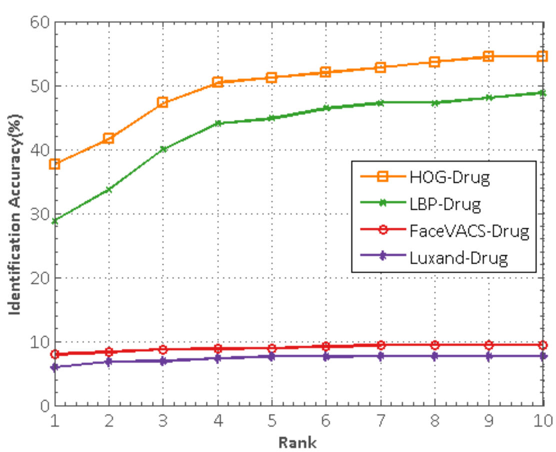

Figure 4. CMC curves for *Drug Faces* Scenario when two COTS, FaceVACS [5] and Luxand [12], and two face descriptors, LBP [13] and HOG [6] are used. It is seen that very few subjects have been correctly identified.

rent facial recognition systems. In this section, we propose a **D**ictionary learning based illicit **D**rug **A**buse face **C**lassification (DDAC) framework where the goal is to separate the face images into two categories, namely *drug-abuse* and *regular*. This can be considered as a filtering process where these images can be matched differently using individually tailored adaptive algorithms for improved face recognition performance. The DDAC framework, shown in Figure 5, comprises of the following steps:

Step 1: Face pre-processing by performing alignment and normalization.

Step 2: Facial regions of interest (ROIs) extraction.

Step 3: ROI based multi-scale Binarized Statistical Image Features (BSIF) [10] and GIST [14] feature computation.

Step 4: Learning multi-scale Binarized Statistical Image Features (BSIF) and GIST specific paired dictionaries to detect possible instances of illicit drug abuse faces from a combined face database.

Step 5: Combining decisions from the learned paired dictionaries.

3.1. Pre-processing and Extraction of Facial Regions of Interest

Faces are pre-processed by converting them to grayscale. All the faces are geometrically aligned by performing landmark detection [19]. This is followed by normalization and background masking using CSU Face Identification Evaluation System [4].

Prolonged illicit drug abuse may lead to significant changes in facial features such as pronounced wrinkles, blisters, and scarring. The facial regions that are more likely to be altered due to illicit drug abuse are chosen as regions of interest (ROIs). The five selected ROIs showing most prominent variations are full face (R1), binocular region (R2), right cheek (R3), left cheek (R4), and forehead (R5). For each face image, these five local and global ROIs are extracted for feature computations and classification.

3.2. Computation of Multiple Discriminatory Features

In the proposed approach, two features are extracted and used for classification: Binarized Statistical Image Features (BSIF) [10] and GIST descriptor [14]. The effect of extensive abuse of drugs may cause accelerated aging, open sores, blisters, blemishes, and scarring on the faces. To model the textural changes and deformations occurring due to these variations, multi-scale BSIF and GIST are computed on the five local and global ROIs.

Binarized Statistical Image Features (BSIF) [10] are gaining popularity as an efficient texture feature in the field of computer vision. In this approach, each element of the binary code is calculated by binarizing the output of a linear filter with thresholding. Each bit of the code denotes a different filter by projecting the image patches to a subspace. Statistical properties of natural images decide the binary code because the set of filters are learned from natural images by maximizing the statistical independence of the responses. Due to this property, statistically meaningful texture information can be learned from the data. The number of filters is an important parameter in BSIF. Using a single filter in BSIF may not encode sufficient discriminatory textural information. Hence, BSIF can be computed at multiple scales (multi-scale BSIF) to enhance the representation of the textural model.

On the other hand, the idea behind GIST descriptor [14] is to learn a low dimensional representation of an image. It also encodes the shape and structure of the image. The descriptor combines statistical information of the responses of filters. It is used to obtain a coarse vector encoding of distributions of different filter orientations and scales in the scene. In order to compute GIST descriptor, a pre-filtering scheme described below is applied to remove illumination variations.

$$I'(x,y) = \frac{I(x,y) \times f(x,y)}{\epsilon + \sqrt{[I(x,y) \times f(x,y)]^2 \times g(x,y)}} \qquad (1)$$

where, $I(x,y)$ is the input image, $g(x,y)$ is a low pass Gaussian filter, and $f(x,y) = 1 - g(x,y)$ is the corresponding high pass filter. The image is divided into 16 blocks. A set of 32 Gabor filters with 4 different scales and 8 different orientations are used to convolve with each of the 16 blocks and the mean moment is concatenated to form the resultant feature vector.

3.3. Feature Specific Paired Dictionary Learning

The proposed DDAC framework performs a filtering step to classify faces in a large dataset under two categories, namely *drug-abuse* faces and *regular* faces. This important step needs to be reliable and fast in terms of computation.

Gu et. al. [8] described a projective dictionary pair learning (DPL) framework. In their approach, joint learning of analysis and synthesis dictionaries is performed to learn representations through linear projection without using the non-linear sparse encodings. The model can be described as:

$$\{\boldsymbol{A}^*, \boldsymbol{S}^*\} = \arg\min_{\boldsymbol{A},\boldsymbol{S}} \sum_{k=1}^{K} \| \boldsymbol{X}_k - \boldsymbol{S}_k \boldsymbol{A}_k \boldsymbol{X}_k \|_F^2 + \beta \| \boldsymbol{A}_k \bar{\boldsymbol{X}}_k \|_F^2, \quad s.t \| \boldsymbol{d}_i \|_2^2 \leq 1 \qquad (2)$$

where, $\boldsymbol{S}$ represents the synthesis dictionary used to reconstruct $\boldsymbol{X}$; $\boldsymbol{A}$ represents the analysis dictionary used to code $\boldsymbol{X}$; $\boldsymbol{A_k}$ and $\boldsymbol{S_k}$ represent the sub-dictionary pair corresponding to class k; $\bar{\boldsymbol{X}}_{\boldsymbol{k}}$ represents the complementary data matrix of $\boldsymbol{X}_k$ in the training set; $\beta{>}0$ is a scalar constant that denotes the regularization parameter to control the discriminative property of $\boldsymbol{A}$, and $\boldsymbol{d}_i$ denotes the i^{th} item of synthesis dictionary $\boldsymbol{S}$. The role of the analysis dictionary $\boldsymbol{A}$ is to help in discrimination, where the sub-dictionary $\boldsymbol{A_k}$ can project the samples from class $i, i \neq k$ to a null space. The role of the synthesis dictionary $\boldsymbol{S}$ is to minimize the reconstruction error.

Two separate paired dictionaries $D^B = \{S^B, A^B\}$ and $D^G = \{S^G, A^G\}$ are learned using multi-scale BSIF and GIST features, respectively. These dictionaries are then utilized for classification and their individual decisions are combined using decision level fusion. The advantage of the proposed DDAC framework lies in its computation time because the framework does not contain any l_0 or l_1 norm. Since the classification scheme is being proposed as a filtering step to categorize *regular* faces and *drug-abuse* faces, the proposed approach is fast and is suitable for real-time applications.

3.4. Illicit Drug Abuse Face Classification and Decision-Level Fusion

Reliable illicit drug abuse face classification is performed using dictionaries D^B and D^G separately. Let $\boldsymbol{y}$ be the testing image and Y_{BSIF} and Y_{GIST} refer to the class prediction labels from the dictionaries D^B and D^G, respectively. The detection of illicit drug abuse faces can be calculated using the following classification scheme:

$$Y_{BSIF} = \text{argmin} \| \boldsymbol{y} - \mathbf{S^B A^B} \boldsymbol{y} \|_2 \qquad (3)$$

$$Y_{GIST} = \text{argmin} \| \boldsymbol{y} - \mathbf{S^G A^G} \boldsymbol{y} \|_2 \qquad (4)$$

While there can be multiple ways of combining the output of dictionaries, we combine them using decision-level fusion [9]. Logical OR is applied on the two decisions to obtain a final decision of whether the given face image belongs to *drug-abuse* face category or not.

$$Y_{DRUG} = Y_{GIST} \vee Y_{BSIF}$$

4. Experimental Results

4.1. Experimental Setup

To evaluate the detection performance of the proposed Dictionary Learning based Illicit Drug Abuse Face Classification (DDAC) framework and simulate the real world scenario, two types of face images are used: IDAF database and regular face database. One *before* and one *after* images of 105 subjects from the IDAF database and the first 105 subjects from CMU Multi-PIE [7] face database are utilized to form the combined face database. Two images with neutral expression, frontal pose, and proper illumination are selected from CMU Multi-PIE [7] face database.

For the purpose of this experiment, unseen training and testing is performed with five-fold cross validation. Images from the combined database of illicit drug abuse faces and regular faces are pre-processed. Five ROIs (full face, binocular region, right cheek, left cheek, and forehead) are extracted from each face image. For each ROI, BSIF is computed at multiple scales of 3, 5, 7, and 11 and the feature vectors are concatenated. Using the concatenated feature vector, two separate dictionaries are learned where the *after* images from the IDAF dataset are considered as one class (positive class) while the remaining data points are combined to form the negative class. Also, GIST features for each ROIs are calculated. Similarly, GIST based paired dictionary is learned to classify possible drug abuse face images. The classification results from the two learned dictionary are combined using an OR operator to yield a final classification decision.

4.1.1 Results and Analysis

- Average classification accuracy, across five folds, of whether a given face image is affected by drug abuse or not is reported in Table 1. For comparison purposes, classification accuracies obtained using commonly used texture and face descriptors such as multi-scale BSIF [10], HOG [6], Self-Similarity [16], GIST [14], and LBP [13] are also shown. From Table 1, it is observed that the proposed DDAC framework yields the highest accuracy of 88.81% and outperforms the commonly used image descriptors. Multi-scale BSIF [10] with SVM yields an accuracy of 75.00%. Similarly, HOG [6], Self-Similarity [16], GIST [14], and LBP [13] yield detection accuracy of 76.90%, 78.01%, 81.09%, and 81.41% respectively.

- The proposed DDAC framework is also compared with the performance of paired dictionary learned on multi-scale BSIF, GIST, Self-Similarity, HOG, and LBP separately. Classification accuracy of 86.38% is observed with learned paired dictionary with multi-scale BSIF and 85.12% is observed with learned paired dictionary with GIST.

- Further analysis is performed on the output of the proposed framework. The proposed DDAC framework correctly classified 80.95% of illicit drug abuse face images (true positive rate) whereas, 92.06% of regular faces are correctly detected as negative class (true negative rate). Figure 6 shows sample images from classes *drug-abuse faces* and *regular faces* which are correctly and incorrectly classified.

- The proposed illicit drug abuse face classification framework uses decision-level fusion to combine the outputs from multi-scale BSIF learned dictionary and GIST learned dictionary. For comparison purposes, sum rule fusion is also applied on the two classification outputs. From Table 1, it is observed that the accuracy using sum rule fusion is 85.84%.

- Computationally, the proposed algorithm requires 0.59 seconds for classifying one image on a desktop PC with 3.4 GHz Intel CPU and 16 GB memory. This includes extraction of multi-scale BSIF and GIST features for the five local and global ROIs.

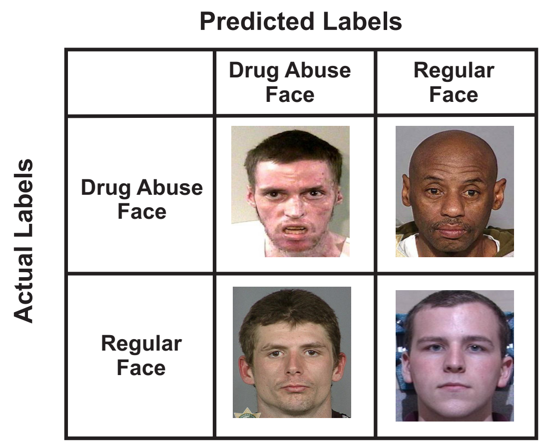

Figure 6. Sample images from classes *drug-abuse faces* and *regular faces* which are correctly and incorrectly classified by the proposed DDAC framework.

5. Conclusion

Researchers have extensively studied the effect of variations such as illumination, age, pose and expressions on the performance of face recognition system. In this paper, we introduce the Illicit Drug Abuse Face (IDAF) dataset and present the effect of illicit drug abuse as another challenge of face recognition. In the current scenario, illicit drug abuse has become one of the major health and social concerns in the world. As seen in the before and after face images, abuse of drugs drastically alters the facial features and hence, it is a challenging research issue. Experiments have been performed to show the deterioration in the performance of commercial face recognition algorithms as well as commonly used face descriptors when illicit drug abuse face images are added to the database of regular faces. The results clearly demonstrate the need to further study and mitigate the effect of illicit drug abuse on face recognition algorithms. We also propose a detection framework to seamlessly classify if a given face image is a *regular* face or a *drug-abuse* face. This framework can act as a crucial preprocessing step in mitigating the effect of such images. The proposed DDAC framework gives a classification accuracy of 88.81% when applied on a combined database of illicit drug abuse faces as well as regular faces.

Table 1. Average detection accuracy (%) for illicit drug abuse face classification using different classification algorithms.

Classification Algorithm	**Average Classification Accuracy (%)**
Multi-scale BSIF [10] + SVM	75.00
HOG [6] + SVM	76.90
Self-Similarity [16] + SVM	78.01
GIST [14] + SVM	81.09
LBP [13] + SVM	81.41
Dictionary Learning using LBP	80.48
Dictionary Learning using HOG	83.32
Dictionary Learning using Self-Similarity	84.18
Dictionary Learning using GIST	85.12
Dictionary Learning using Multi-Scale BSIF	86.38
Sum Rule Fusion of Multi-Scale BSIF and GIST Dictionaries	85.84
Proposed DDAC Framework	**88.81**

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