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A Comparison of ANFIS, SVM and KNN models for the face recognition in unconstrained environment

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ABSTRACT

For the rapid extending applications of face recognition as an important technique for identification over other biometric features, different types of databases of images have been generated and published. The existing face datasets can be collected either in controlled environments such that the ones used for drivers' license and passport or unconstrained environments such that with variation in size, position, pose, lighting, expression, background, camera quality, occlusion, age, and gender. Many techniques were proposed to identify different acquired characters, resulting in wide various accuracies and other measures. Supervised machine learning techniques especially Adaptive-network-based fuzzy inference (ANFIS), K-nearest neighbor (KNN|) and support vector machine (SVM) have been widely used as models in this context. In this paper, we study the accuracy result of those models when used in various types of database, and conclude with the best conditions for satisfactory recognition results.

Key words: Constraints classified, Deep learning, Face Recognition, Fuzzy system.

1. INTRODUCTION

Recently, various biometric features to satisfy the high demand of identification and authentication, such features include fingerprint, palm print, hand geometry, iris, face, speech, gates and signature are used to identify human. All those features except face require active cooperation of the person to identify him/her self, thus face recognition got the attraction regardless of its accuracy fluctuation[1],[2],[-3].

The development of computing and computer technologies serve in widely spreading the use of face recognition technology for many security applications; such as bank ATMs', computer or mobile access, computer games, document control like password verification, besides attendance applications by controlling entry and exit process, in addition to election accuracy where voter fraud can be eliminated[4].

Face recognition is defined as the procedure of identifying a specific individual either to be known or unknown. Face recognition has two phases; verification and identification. Face verification is confirming the same person in the scene, while identification who is this person. Thus, the problem of face recognition starts by detecting human faces from the whole scene in an image, then the "similarity" is checked by comparing with other faces in the database. The result of this process is labeling the acquired face by its name or failing to do [5].

To achieve the goal above, many classifiers were developed, the majority of them recline on the concept of extracting face features, then train the classifier to obtain the model, finally, these models are used to predict and recognize the image under question[6]. The training process required the availability of sufficient bank of images for various individuals, thus many researchers randomly collected different databases ranging in size, scope, and purpose, the variation includes size, position, pose, lighting, expression, background, camera quality, occlusion, age and gender [7].

In this work, we investigate the power represented in recognition accuracy of three machines learning classifiers: The k-Nearest Neighbors (KNN), Adaptive-network-based fuzzy inference (ANFIS); and the Super Vector Machine (SVM) when applied to different types of databases, labeled as constrained or unconstrained collection.

In the second section a brief background of KNN, ANFIS and SVM is given, the third section summaries related works with the intended databases, the fourth section explains the used methodology and present simulation results, and finally the work is concluded in the fifth section.

2. CLASSIFICATION

Classification is the problem of identifying to which categories a new observation belongs. It is performed by using supervised learning. Supervised learning is the machine learning framework in which the training data comprises different groups of data labeled as classes, by training, each class has an inferred function which used in mapping new examples to the closer class [8]. In this section, the KNN and SVM are briefly explained.

2.1 The K-Nearest Neighbors (KNN)

This classifier is a simple machine learning algorithm that based on the idea that close objects are similar, so the tested image belongs to the closest class. Euclidean Distance is used as a measure to calculate how close each member of the training set is to the test class that is being examined. Figure 1 demonstrates the meaning of the parameter K in the K-nearest neighbors. By training the different classes in the class space, the common features are extracted, for example, the blue and red ones, the green one is the one to be classified, so the distance" with respect to the nearest three (k=3) is determined by applying majority voting to determine the class label of the test image. K can be changed to seven (K=7) and the procedure is repeated.

The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct [6],[9],[10, 11],[12].

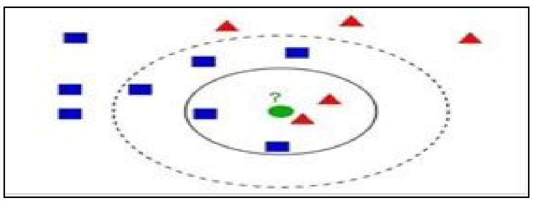


Figure 1: K-Nearest Neighbors [8]

2.2 The Support Vector Machine (SVM)

Support Vector Machines (SVM- gamma='scale') is used for classification and regression analysis. The trained data is divided into categories; SVM builds a model that assigns the tested image to belong to one of the categories. Figure 2 demonstrates the idea of SVM by considering two types of data, red and blue. SVM find a line that uniquely divides the data into two regions. Although, plenty of lines are possible, the approved line is the one that passed as far as possible from all the points. This line has the largest minimum distance to the training samples [6], [9],[10],[12].

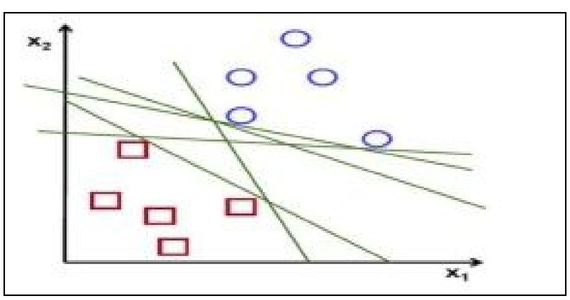


Figure 2: SVM [8]

2.3 ANFIS

ANFIS is a Fuzzy Inference System (FIS) and using Artificial Neural Network [13], [14] , [15],[16] (see please Figure 3).

The rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

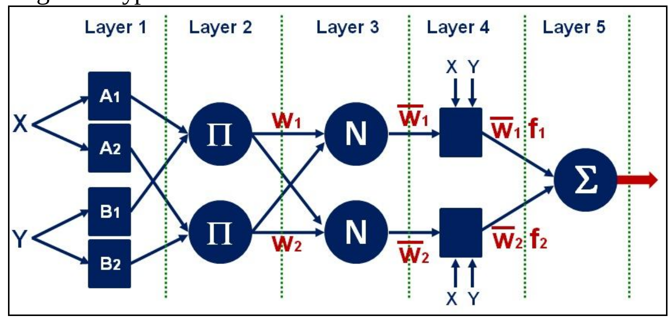


Figure 3: Anfis [17]

$\boldsymbol{Rule1}: if\ x\ is\ \boldsymbol{A_1}\ and\ y\ is\ \boldsymbol{B_1}\ , then\ f_1 = p_1x + q_1y + r_1$

$\boldsymbol{Rule2}: if\ x\ is\ \boldsymbol{A_2}\ and\ y\ is\ \boldsymbol{B_2}\ , then\ f_2 = p_2x + q_2y + r_2$

Where:

$\boldsymbol{x}, \boldsymbol{y}$: Two input data.

f_i: Fuzzy inference according to the desired output.

A_i, B_i: are labels of fuzzy sets characterized by appropriate membership function.

$\mu_{Ai}(x)$:Is the membership functions of A_i.

$$\mu_{Ai}(x) = e^{-(\frac{x-c_i}{a_i})^2}$$

$\{a_i, c_i\}$: Is the parameter set.

<u>Layer1</u>: Generating degree of membership.

$$O_{1,i} = \mu_{Ai}(x)\ , \qquad i = 1,2$$

Where:

$O_{k,i}$: is the node function, where *k* is the number of the layer and *i* is the node position in the layer.

<u>Layer 2</u>: Fuzzy intersection.

$$O_{2,i} = w_i = \mu_{Ai}(x).\mu_{Bi}(x)\ , \qquad i = 1,2$$

<u>Layer3</u>: Normalization.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad i = 1,2$$

<u>Layer4</u>: Defuzzyfication

$$O_{4,i} = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i)$$

Where $\{p_i, q_i, r_i\}$ is the parameters set (consequent parameters)?

<u>Layer 5</u>: The final output

$$O_{5,i} = \sum_i \overline{w_i}f_i = \frac{\sum_i w_if_i}{\sum_i w_i}$$

3. RELATED WORK

Kim et al. used random subsets generated by Aleix Martinez and Robert Benavente or what is called AR face database, and Caltech face database for their high resolution (130x140) images to test their proposed feature-based method to classify salient points in between two classes: face or background (non-face). They utilized (Speeded up Robust Features) SURF descriptors to generate informative feature vectors and use SVM as classifiers [9].

Aarabi et al. performed several experiments using simple detector test on the Caltech Frontal Face database. The detector correctly detected 404 of the 450 images available in the database, without training or pretreatment, gives a detection rate of 90% [12].

Karim et al. study the performance of facial recognition system based on Principal Component Analysis (PCA), using standard databases; Indian Databases and Facial Recognition Data, University of Essex, United Kingdom. They use the SAD, SSD and NeC techniques for the corresponding images. The recognition rate has been satisfactory[18].

R. Padilla et al. used two databases (FEI and yale face). The FEI Face Database is a Brazilian database containing 2800 images including 14 images for 200 people. The images are collected in different rotations with neutral expressions, smiling and not smiling. The authors used 2 frontal images per individual, taking into account the smiling and non-smiling expression, out of a total of 400 images. The Yale database contains facial images of 15 people, with 11 images per person, taken with different lighting conditions. Subjects have different facial expressions (with glasses, sad, sleepy, surprised, wink). The results showed that FEI is higher than yale for non-frontal images [19].

Setty et al. have created the Indian Movie Face database (IMFDB) which includes 34512 faces of 100 known actors, detected manually from 103 films, these images lead to a great variability (scale, pose, expression, illumination, age, occlusion, makeup). IMFDB provides a detailed annotation in terms of age, posture, gender, expression, degree of occlusion [20].

Bianco conducted extensive experiments on Large Age-Gap dataset (LAG) that includes images in the wild of 1010 international celebrities spanning large age gaps to show that the proposed new DCNN architecture with the activations of the deepest DCNN layers can outperform state-of-the- art methods [21].

4. DATABASES

In this work, seven miscellaneous databases are chosen, the target is to choose different levels of constrained within the collected images with different sizes as well. Constrains includes, position, pose, lighting, expression, background, camera quality, occlusion, age, and gender. We categorize the databases according to their characteristics affecting the accuracy of face recognition into critical or uncritical ones. The selected databases with their main characteristics are listed in Table 1.

The seven selected databases are Caltech Faces, CyberExtruder Ultimate Face Matching Data Set, Face Recognition Data, University of Essex, UK, FEI Face Database, IIIT-CFW Database, Large Age-Gap (LAG) dataset and Indian Movie Face Database (IMFDB) [22].

The constrains that clearly appear within the dataset are database size, (both number of images, and number of individuals), change in facial expressions, different ages, obstructions on face (occlusion), age evolution, position of face from camera, orientation of face, different lighting, backgrounds (existing of many objects in images), cartoon (face synthesis, heterogeneous face recognition), and similarity between faces (same race). Based on the description of the databases available in their references, we noticed that some are common in all the selected databases, so they have no effect on the results, and some are distinguished and have major effects on the results as will clarified later.

5. SYSTEM METHODOLOGY

For the machine learning implementation, we use Dlib, and scikit-learn libraries which are an open source library that provide support for developing machine learning software in Python, R, Matlab, and similar environments [23],[24],[25].

In order to detect the position of the faces in the images so as to obtain a region of interest on which the extraction of the feature vectors can be accomplished, the Viola-Jones (JV) detection algorithm [26] is used. This algorithm is based on a series of weak classifiers in cascade having been previously trained according to the AdaBoost technique in order to allow a robust and rapid detection of the faces. For this study, the evaluation of the faces is accomplished by considering the face as a whole. So, the features are extracted for the entire face contained in the region found with Viola-Jones without attempting to represent geometric relationships between the eyes, nose and mouth.

In order to explore new feature extraction methods with the aim of improving face recognition performance, a HOG descriptor[27],[28] is considered in this study. This technique accomplishes a representation of faces using a histogram analysis of the gradients present in the image. More particularly, the region of interest where the face is detected is subdivided into blocks of equal sizes and these are also subdivided into cells. For each of the cells, an analysis of the pixel gradients is performed to form a multi-band gradient histogram.

The block diagram of the system is shown in Figure 4. As mentioned earlier, the process we are using is classification under supervised algorithm; that is, images from database are sorted into classes, each class contain the image of certain individual. Practically this is done by collecting the images that includes the same person in a sub-folder. In the first phase, human face within the whole image is bounded into separate frames and thus, the features of each face -which is called landmarks- are extracted. Those landmarks are manipulated to come up with remarkable identity (function) for each class. This stage is called “training”, and a Python function called “train” is used to implement this action.

In the next phase, the classifier (KNN or SVM in our case); which finds a way to relate the face under question to its closest class, and marks it with the name of that class. If the classifier failed to find a close matching with one of the available classes, the face will be marked as "unknown". The Euclidean distances between the query instance and the training samples are calculated to predict the test data classes and sorted according to the smallest difference to determine the nearest neighbor Kth.

Anfis was particularly difficult to implement under python, considering that it was only available under MATLAB.

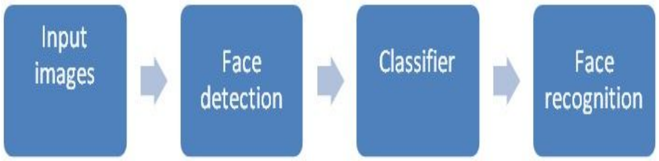


Figure 4 : Block Diagram of Recognition System

6. SIMULATION AND RESULTS

Our target is to measure the accuracy of recognition for the supervised classifiers KNN and SVM built in the Python library scikit-learn and Anfis in MATLAB, with minimum modification when applied to different constrains of an image. We use 20% of the database for testing, the choice of images was random, and 80% for learning. When we apply the KNN algorithm, we tested various K-parameter which represents the number of nearest neighbors, and recorded the accuracy of the results as well. This advises the later users of these classifiers if it is necessary to change K or keep it at its default value.

The experiments show relatively close results for both classifiers, but it is noticeable that the simulation time for the SVM classifier is much less than that for KNN classifier and Anfis which require longer training time. Here below, we will investigate the result obtained for each database and discuss the reason upon that result.

6.1 Caltech Faces

Seventeen images on average for each individual are available in this database, so the training is not very high. Although the characters' faces belong to different ages, with different face expressions, and the photos were taken in different lighting conditions with different background. The recognition accuracy is highly optimistic, 98% Anfis, 98% for KNN and 96% SVM. This can be attributed to the wide range of races for individual in the database; i.e. people features are distinct and the tested image can be easily classified to its correct class.

6.2. CyberExtruder Ultimate Face Matching Data Set

In this database, 1000 high resolution images on average for each individual are available, so the system has condensed training. In addition, the data set contains large variations in pose, lighting, expression, race and age. It also contains images with multitude of occlusion (hats, glasses, makeup), and face orientation with different angles. In spite of those variations, the accuracy is very high, around 100% for Anfis, KNN and SVM. This is due to the fact that the database is large and with few similarities between faces, which results in accurate training. Some examples of the test are shown in figure 6.

6.3. Face Recognition Data, University of Essex, UK

Face Recognition Data, University of Essex, UK database has an average of 20 images per individual. The images belong mostly to male and female in the range of 18-20 years old of various racial origin, some individuals wearing glasses and beards. All the images are frontal, thus ANFIS, KNN and SVM algorithms came up with very high accuracy recognition 100%. Although, many images are taken with low brightness, but not to the level that will vanish the main features of the face that extracted in the training phase.

6.4. FEI Face Database

Fourteen high resolution images on average of each individual are available in this database, so, again, the training is not very high. The set contains distinct faces for male and female individuals in the range of 19 to 40 years old. The results are highly affected by the profile orientation that reach up to about 180 degrees. In this case, ANFIS shows a bit higher accuracy than KNN and SVM; 95%, 90% 93% and respectively.

6.5. IIIT Cartoon Faces In The Wild

The IIIT-CFW is database for the cartoon faces of 100 celebrities, on average of 89 images per person including their real and cartoon profiles. This database is found to have a challenging recognition problem when KNN and SVM are directly applied in their default manner. ANFIS results in a better accuracy -around 71% - against 55% with KNN and 62% with SVM. The problem in this database that the features are very difficult to be extract. More modified and advanced algorithms need to be considered such as in [7],[22],[29]. Examples of the results obtained are shown in figure 8.

6.6. Large Age-Gap Database (LAG)

The most important feature of Large Age-Gap (LAG) dataset is that it contains individual with wide variations in age[30]; which results in wide diversity in the extracted features for the same person. The major problem facing the classifiers here is the lack of data, since less than 4 images on average per person are available. Both classifiers failed to success in matching the tested image to its appropriate class. The results obtained are 63%, 58% and 44% for ANFIS, SVM and KNN respectively. Changing the threshold for SVM or K for KNN didn't improve the results. Some examples of the test are shown in figure 7.

6.7. Indian Movie Face database (IMFDB)

This database is the largest database among the ones used in this work; around 345 image per Indian actor collected from videos, but plenty of them have low resolution or comes in small scale. It also contains high degree of variability in scale, pose, expression, illumination, age, resolution, occlusion, and makeup for the same race of people (Indian). The results for this database are the worst among the tested ones; the recognition accuracy is 55% using ANFIS and 37%, 26% using SVM and KNN. The reason behind such result is the combination of many challenging constrains; the similarity, occlusion, and orientation. Some examples of the test are shown in figure 9.

By relating Table 1 which includes the databases and the images constrains in each, with the Face detection accuracy results, we can separate the constrains into two classes; the former has high influence on the accuracy, while the later has low influence. This point is summarized as:

Constraints classified as 'Low' are: The Change in Facial Expressions, Different Ages, Position of Face of Camera, Orientation of Face, Different Lighting and Backgrounds. The detection algorithm of the face recognition is very robust to eliminate these constraints.

Constraints classified as 'high' are: The Database Size of Images, Variety of Individuals, Obstructions on Face, Age Evolution, Cartoon (face synthesis, heterogeneous face recognition), and Similarity between Faces (same race). The face detection algorithm is highly influenced by occlusion and the cartoon and the recognition-learning algorithm (ANFIS, SVM and KNN) is strongly influenced by the size of the database and the number of individuals (classes) in each database. For example, in the database 'Large Age-Gap (LAG) dataset' the number of images = 3828 images, and the number of individuals = 1000, so for each individual, the number of image equals to three, this can be considered low for learning and therefore a low detection rate is observed. Another example is 'IIIT-CFW database' the number of images for each individual is very high 8928/100 = 90 images for each individual but the presence of the cartoon constraint makes the definition of descriptor for each individual very difficult. Yet another example, for the 'Indian Movie Face Database (IMFDB)' the similarity and likeness of faces make the recognition difficult.

When considering KNN classifier, test is performed for K=3, 10, 15, 20 and 25, and the results versus accuracy percentage is plotted in figure 5. It is shown that the accuracy lightly decreases as K increases. This is because when K increases, more information are involved in the comparison, this makes the recognition more complex and it is more probably to fail to match with the correct image, and thus, accuracy decreases.

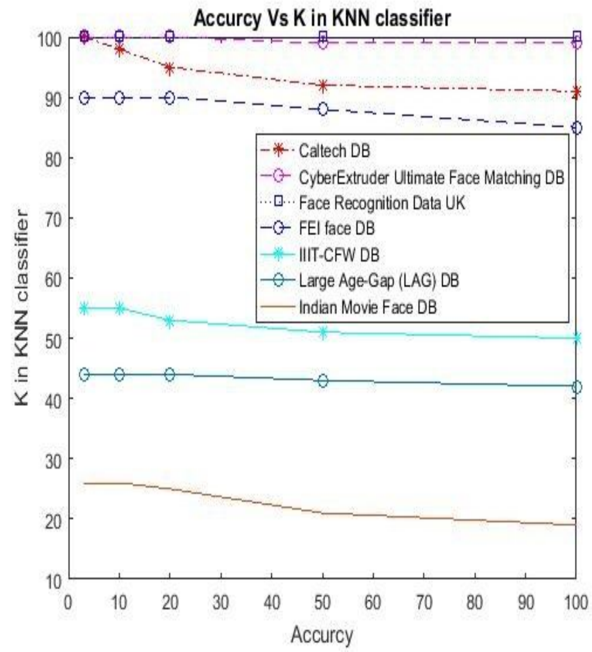


Figure 5: Increasing K for Different Database

7. CONCLUSION

In this study, two classifiers built in machine learning under Python and ANFIS under MATLAB environment were applied to seven selected databases of images acquired under different environmental constrains. The classifiers that were used for testing are KNN and SVM. The KNN uses the Euclidean distance measurement of the characteristic features and the SVM maximizes the separation margin of the data to be classified. The resulted recognition accuracy is highly related to the image constrains. The constrains were categorize into two sets denoted as "high" and "low" depending on their effect on the results. The "high" are those constrains that critically affect the results. It is recommended to consider the 'high' constrains when dealing with critical application such as surveillance. KNN showed good predictive accuracy in small dimension large data sets but not in large data sets, since in a large data set, it is difficult to describe the descriptor's vector of each individual.

The ANFI seems more successful than the MLP and SVM if the lack of data exists or if the size of the database is small. The ANFIS is used to adjust the weights and approximates more and more to produce the desired output, it should be preferred due to its fuzzy logic capability that manages the uncertainty of fuzzy data, ambiguous or incomplete. The size of the basic rules is crucial to the computational charge, for this reason, this method is appropriate for problems with relatively have a small number of input variables.

For future work, more databases are going to be considered in the study, and a clustering technique may need to be apply prior to the classification, so that clearer results and their dependency on the image features and constrains will be concluded. Also, it is suggested to include more features, 3D for example, to distinguish between individual when great similarities between individuals may exist.

Table 1: Databases and their characteristics

DATABASE / CONSTRAIN TYPE	CALTECH FACES	CYBEREXTRUDER ULTIMATE FACE MATCHING DATA SET	FACE RECOGNITION DATA, UNIVERSITY OF ESSEX, UK	FEI FACE DATABASE	IIIT-CFW DATABASE	LARGE AGE-GAP (LAG) DATASET	INDIAN MOVIE FACE DATABASE (IMFDB)
DATABASE SIZE OF IMAGES	450	10205	7900	2800	8928	3828	34512
VARIETY OF INDIVIDUALS	27	1000	395	200	100	1010	100
CHANGE IN FACIAL EXPRESSIONS	YES	YES	YES	YES	YES	YES	YES
DIFFERENT AGES	YES	YES	YES	BETWEEN19 AND 40 YEARS OLD	YES	YES	YES
OBSTRUCTIONS ON FACE (OCCLUSION)	NO	YES	NO	NO	YES	NO	YES
AGE EVOLUTION	NO	NO	NO	NO	NO	YES	NO
POSITION OF FACE FROM CAMERA	CLOSE	VERY CLOSE	VERY CLOSE	VERY CLOSE	VERY CLOSE	VERY CLOSE	VERY CLOSE
ORIENTATION OF FACE	NO	YES	NO	YES	YES	YES	YES
DIFFERENT LIGHTING	YES	YES	YES	YES	YES	YES	YES
BACKGROUNDS (EXISTING OF MANY OBJECTS IN IMAGES)	YES	NO	NO	NO	NO	NO	NO
CARTOON (FACE SYNTHESIS, HETEROGENEOUS FACE RECOGNITION)	NO	NO	NO	NO	YES	NO	NO
SIMILARITY BETWEEN FACES (SAME RACE)	NO	NO	NO	NO	NO	NO	YES (INDIAN)

TRAIN (ORIGINAL FACE)	TEST	RESULT
		OK
		OK
		OK
		OK
		OK

Figure 6: Cyber Extruder Ultimate database examples

TRAIN (ORIGINAL FACE)	TEST	RESULT
		NO Correct name: AGYNESS DEYN
		NO Correct name: ALAIN VODONAEVA
		OK
		NO Correct name: ADAM LEVINE
		NO Correct name: AALIYAH

Figure 7: Examples for results for LARGE-AGE GAP database

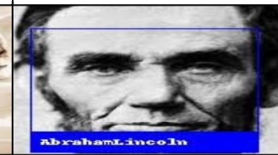
TRAIN (ORIGINAL FACE)	TEST	RESULT
		OK
		OK
		NO Correct name: ANGELA MERKEL
		NO Correct name: JKROWLING
		NO Correct name: MOHAMED ALI

Figure 8: Examples of results for IIIT CARTOONS DATABE

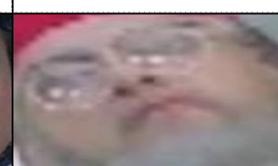
TRAIN (ORIGINAL FACE)	TEST	RESULT
		NO Not clear image
		NO Small size 27x42 Not detectable
		NO Correct name: HIDDENEYES
		NO Correct name: AMBAREESH
		OK

Figure 9: Example for tested images using IMFDB database

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