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Authentication System by Facial Recognition with Principal Component Analysis and Deep Neural Networks

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Abstract: The requirement for a facial recognition framework is reliable in terms of in-plane head lighting and movement conditions; has increased as a result of recent technological advancements and rising business demand. Principal Component Analysis (PCA) and neural networks are both used in the proposed and validated face recognition approach. In the suggested method, significant facial features are extracted, their dimensions are reduced using PCA, and then the facial features are classified using neural networks. The algorithm's outcomes are compiled and contrasted with those of other algorithms that were evaluated on the same dataset, particularly the well-known eigenfaces method and a convolutional neural network approach. We find that the suggested method can train significantly more quickly than the convolutional neural network method and can achieve a higher successful rate than either of the other two methods. The paper includes a discussion and comparison of the findings as well as a procedure walkthrough of the way the research was carried out.

Keywords: *Authentication, Facial Recognition, Neural Networks, Pattern Recognition, Deep Learning.*

1. Introduction

In computer science, face recognition is a challenging topic. Recent technological developments have enabled us to enhance our facial recognition infrastructure and algorithms significantly. Unfortunately, face recognition systems usually run into its own unique issues when used for security purposes. Some of these issues are caused by the input data in that we will not always have the cooperation of the individual. For these reasons, this paper introduces a new strategy for facial recognition that is more efficient and robust.

Facial recognition involves using computer algorithms to identify a person using their facial features, such as the distance of their brows. In such face recognition, there are two major issues; representation and matching. These issues must be fully resolved to rid the problem of facial recognition.

There are several methods of personal biometric identifications. Those that depend on scanning fingerprints and iris are notable examples. Unfortunately, these methods greatly rely on the person consenting to the scans. As such, their use is largely limited, especially in crime detection among large populaces. Such makes facial recognition very promising, since it can be done without the person’s consent and knowledge. As such, it can even be used in identifying suspects in CCTV footages, since it can scan many people.

Another concern that frequently occurs in facial recognition, additional features are being added, items, such as hats, facial hair, or glasses. These objects usually obstruct certain face regions, thereby making facial recognition difficult [1]. Often, developers try to rid of the issue by segmenting the face into various parts and using them to identify the person, rather than trying to use the whole face.

Face recognition suffers from two fundamental issues: recognition and verification. Recognition denotes the ability to identify a person, while verification refers to the ability to assess whether they exist in the system. The latter stems from the fact that it is impossible to identify a person with absolute certainty in a database. Therefore, the system usually picks the closest match. This issue is problematic in security, as it would identify several people who are close to the match. In order to eliminate concerns that are below a certain proportion yet match people in the database, some type of thresholding method must be used.

King and Xu [2] give a biological justification for normalizing the lighting in an image, which is that the human irisi usually stretches and contracts to regulate the light quantity entering the eye.

The format of images is frequently not suitable for direct entry into a recognition algorithm. The illumination in the test image might differ from the sample data used to train the algorithm, and there might be more information in the image than just one face. As a result, an image must be preprocessed in order to eliminate noise, normalize lighting, and acquire the best results before being sent into a recognition algorithm.

Compared to faces light from the bottom, top-lit faces are easier to recognize. The image can be normalized using a variety of techniques in an effort to minimize illumination variations in the image. To ensure that each stochastic range value reflects an several similar times, histogram normalization was developed.

Notably, King and Xu [2] give a biological justification for normalizing the lighting in an image. This justification is that the human iris usually stretches and contracts to regulate the light quantity entering the eye.

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The image's resolution needs to be good to allow any significant characteristics to be identified. If the image's resolution is high or processing the image takes long time, the algorithm may end up relying on insignificant features of a face to identify it. Noise that is present in the input image must be removed, especially if it is inconsistent across all photos. Images can be transformed to the Fourier domain, selected points can be deleted, and then periodic noise is removed by returning the image to the original size. The majority of other noises kinds can be eliminated or reduced by using employing a variety of image-smoothing filters.

Another crucial factor that can impact a system's identification rate is the size and scale of the face. Therefore, one must identify and normalize faces in images and make an effort to remove as much background as feasible.

The most promising settings for face detection and recognition right now is PCA. Even though it has significant limitations, it is quick and, provided the training data is in the right format, can yield good results.

Additionally, certain features can be located using the geometric structure of the face. The fact that the lips and eyes make an isosceles triangle could be used in an algorithm for frontal view face detection. We can also take use of the fact that the height-proportionality of the distance between the centers of the two eyes and the lips on most faces. However, these techniques presuppose essential features like the eyes and lips can be seen clearly in the photograph and aren't hidden by clothing or hair [3]. This technique might also produce a large number of false positives, particularly if the image has many details besides the face.

The thresholding strategy [3] has two parts: low thresholding and high thresholding. Use high thresholding to define the boundary of the head; low thresholding to determine the contour of the features of the face. This method may fill in any gaps since it makes use of the head's circular shape.

A computational decision-maker called a neural network is based on many layers. Numbers are received as inputs at the input layer, where they are subjected to multiple thresholds and weights at each node before being transmitted to the output layer.

Self-Organizing Maps (SOM) are suggested by Lawrence et al. [4] to both minimize the size of the input image and generate invariance to little changes in the face. Character recognition has successfully used convolutional networks [4]. There are several levels in the network, and each level has one or more planes. The provided data needs to be standardized and centered. Each layer's plane receives data from a small fraction of the layer below. You may think of each plane as a feature map.

2. Related Literatures

One of the most extensively researched fields in computer vision and machine learning since the 1970s is face recognition. Numerous initiatives have been made to increase the dependability and durability of facial recognition technologies [5]. We tested the effectiveness of the hand-crafted methods for face classification that have been used for a long time, such as edges and contours. Deep learning approaches are increasingly being used to replace more conventional ones, a notable one being the convolutional neural network [6]. Admittedly, the present uses of facial recognition technology, could be significantly enhanced by automated deep learning-based facial recognition systems. The following subsections categorically address conventional and cutting-edge facial recognition methods.

Automatic facial recognition techniques based on geometric features were first utilized in the early 1970s. These techniques rely on specific edges and parts of the face, from which the location and distance of facial landmarks were determined. They transform the facial image into geometric primitives, identifying the location of the eyes, nose, and mouth and noting where they are on the face. Even though it was created on a tiny dataset with only ten patients, the results were correct [6]. In the method suggested, appearance-based characteristics are used. Comparing the geometry-based process to the appearance-based method, the former is quicker and uses less storage.

Holistic approaches substitute 2-D matrices for 3-D geometry to express faces. It breaks down a face image into Eigenfaces, which are fundamental building blocks for facial recognition system training. For face recognition, a fresh image is projected into the area covered by Eigenfaces and compared to where a known person is. The eigenvectors are groups of characteristics that emphasize differences between face photos [7]. Each image's position contributes to the Eigenvectors, shown as spectral faces called Eigenfaces. Information theory methods provide information about significant local and global facial features that may or may not be connected to our intuitive understanding of features like the eyes, nose, and lips.

Principal Component Analysis (PCA) and Linear Discriminant Analysis are combined in holistic approaches based on Fisher Discriminant Analysis (LDA). Moreover, LDA maximizes class variation, uses the feature set, thus PCA decreases the feature set's dimensionality. Data with variations are categorized by eigenvectors and showcased by PCA to their matching greatest eigenvalue in the covariance matrix [7]. When there is significant intra-class heterogeneity, these approaches suffer greatly. To create linearly separated classes, the fisher linear discriminant maximizes the split matrix spacing between subclasses while concurrently minimizing the distance within a class distribution. However, these approaches have several limitations, such as PCA's tendency to exclude specific crucial data, the difficulty in using fisher face, and its incapacity to adapt to changes in lighting conditions.

Comparing feature extraction approaches to holistic processes, they are more robust in capturing fluctuations in facial characteristics since they extract discriminative features other than analyzing their geometry. The Shift Invariant Feature Transform (SIFT) descriptor resolves key machine vision issues such as views of 3-D objects [8]. It is less expensive and easier to execute because feature extraction is done in a cascade fashion and expensive operations are only used where the exciting point is [9].

The Speeded Up Robust Features are built on automatic scale recognition, which is both speedier and more recognizable (SURF). Calculation time is decreased by using integral images in conjunction with the Hessian detector for scale detection. Rotation invariance of SURF is achieved by incorporating Haar wavelet responses. In order to classify sections of an image, Haar-like features accumulate the pixel intensities in each adjacent rectangular region in a detection window at a predetermined point in the image, and then calculate the difference between these sums [8]. Ada boost reduces calculation times by removing extraneous features from each detected window of an image depending on their relative weights during processing. All phases or emphases, including extraction, use the selected highlights to record computations and accelerate.

Before the utilization of profound learning for face acknowledgment, mixes of all-encompassing strategies and component-based techniques were utilized to join their free properties and limit the impacts of their deficiencies for further developed acknowledgment execution. Extricating neighborhood highlights utilizing SIFT and deploying them on a lower layered subspace utilizing PCA is one of the most famous half-and-half methodologies. A few blending methods also combined Gabor wavelet highlights with other subspaces that were obtained by convolving a Gabor chunk with the image at various readings and orientations. Additionally, Laplacian PCA and LDA subspaces were projected onto, and connected to, Local Binary Pattern (LBP) descriptors at various targets [10] [11]. Three fix LBP and four fixes LBP were joined with LDA and SVM to help acknowledge exactness by encoding similitudes between adjoining patches of pixels.

Convolutional Neural Network (CNN) is the most broadly utilized profound brain network that can extricate undeniable level delegate highlights from massive datasets and is invariant to brightening variety, brilliance variety, age variety, and facial direction. The exhibition of a profound studying technique is extended by expanding types and the size of the dataset [12]. As such, CNN-based learning frameworks are otherwise called start-to-finish teachable frameworks. There uses vary, such as in the arrangement approach which includes an expectation of class names of info tests.

The preceding CNN, probabilistic choice-based brain organizations (PBDNN) are utilized for facial acknowledgment, eye restriction, and face identification. More extensive datasets with all potential picture varieties are expected to learn more powerful elements in profound learning strategies. In brain organizations, the misfortune capability estimates mistakes between anticipated esteem and genuine worth. Brain networks utilize educational inclination drop and expect to pick misfortune capability while planning a model. The decision of misfortune capability is likewise a significant choice when planning a brain network design [12]. SoftMax is a well-known misfortune capability that is generally utilized in CNN structures. The preparation season of CNN is typically exceptionally high, thus diminished by moving learning in tweaking pre-prepared models on a new dataset. Some recent applications for using CNN in facial recognition systems are secured mobile banking [13], person identification system [14], preventing respiratory viral infections [15], and many more new trends.

3. Proposed Method

The AT&T face database will be used to test the algorithm. Figure 1 displays a few subjects taken from the database. Each of the 40 topics in this database has ten different images. The lighting, face angle, and facial expressions in the images vary only a little. The faces are not always centered in the images in the database since there is a side-headed movement within the image. At least one person's photos with and without glasses may be found in the database. Several tests will be run, each using a different set of images for testing and training. As test images, both recognized and hidden, there will be faces. The following is a definition of the successful recognition rate:

$$Recognition\ rate = \frac{Number\ of\ correctly\ recognized\ images}{Total\ number\ of\ images\ tested}$$

We will put our suggested approach, recognition by a single neural network, and Turk and Pentland's [16] eigenfaces method all into practice. This will enable us to compare the outcomes of each procedure using the same database and set of parameters. To reach running and training times for the algorithm, we will specifically need to implement all three approaches in the same environment.

We will track the following data for each method run: percentage of recognition rate without applying acceptance rate, percentage of recognition rate after applying acceptance rate, average running time, and average training time. For every individual in the database, each framework will be performed fifty times, and the average of the aforementioned numbers will be determined.

At each run, a random selection of the subjects and images will be used for training and testing. To ascertain the false acceptance rate of the system, fifteen individuals who were not utilized in training will be chosen randomly and tested using the recognition framework. The identity of an input image will be identified using a Euclidean minimum-distance approach, and an ideal value of threshold will be found to enhance identification rates and reduce false acceptance rates. The input image will be accepted if the Euclidean distance is less than the threshold; else, it will be refused.

Fig. 1. Sample images of AT&T database.

We will test the system once again, utilizing the database of thirty users. Each person will have six photos utilized for training as well as three images used for testing. On each run, a random selection will be made for the photos and the individuals included in the system's training and testing. Ten users are covert tests to estimate the system's false acceptance rate, while the remaining twenty are chosen to receive harmful training materials.

Before inserting the image into the network, histogram equalization is done to adjust the illumination. A single face image measuring 100 by 100 pixels serves as the neural network's input. The network thus has 10000 inputs and one hidden layer of 100 neurons. The number of individuals the system can recognize is directly correlated with the number of neurons in the output layer. The output values of the network range from (-1,1). The input will be acknowledged and counted if the system's output exceeds a predefined threshold.

Thirty database users will once again be used to evaluate the framework, and all test subjects and photos will be picked at random at the beginning of each session. The network pattern is honed to have absolute error under 0.0001. On some runs, it is impossible to train the pattern network to the required function value performance. The network is tested and trained using all the data, thus after training, its weights are reset and it is retrained, if required.

4. Results and discussions

Figure 2 shows the percentage of the percentage of successful rates of the PCA, CCN, and the proposed method. It shows that the proposed method outflanks the other two methods with enhancement 2.45% over the CNN and 8.67% over the PCA. Even though the figure shows the three methods have acceptable recognition rate, combining CNN and PCA generated a robust method to overcome many factors' influences on the selected features like lighting and others.

A security face recognition system must be able to reject users who have not been granted access in order to work. Acceptance rate is the process used to do this. The person who is recognized is rejected if they fall below a set acceptance rate. However, this can have a negative impact on the system's recognition rate. Even if a person is accurately recognized, the system must reject him if his recognition value is below the acceptance rate since it cannot verify his validity as shown in figure 3.

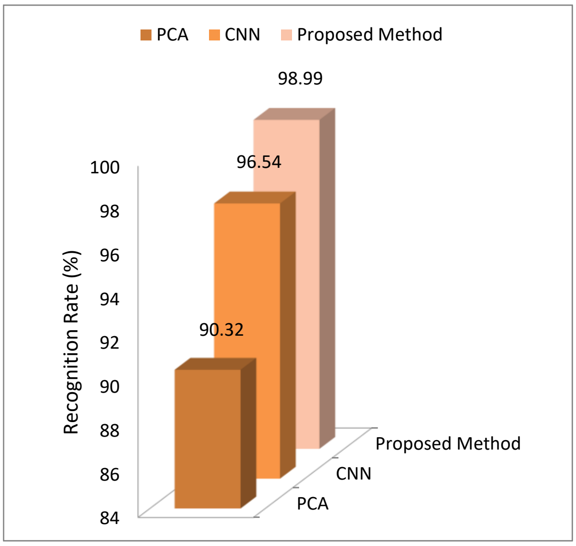

Fig. 2. Percentage of recognition rates of the three methods.

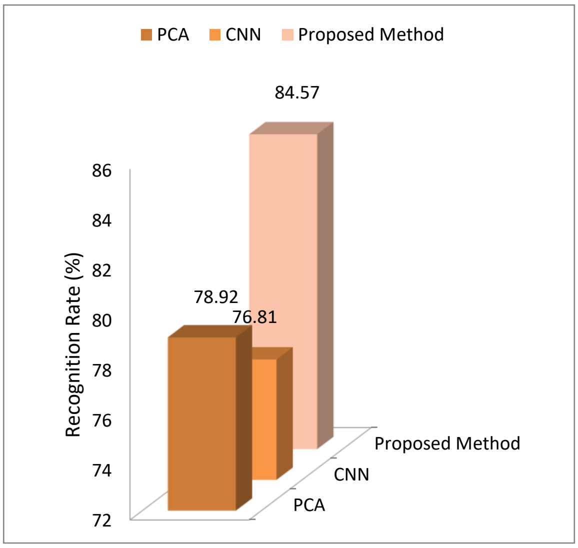

Fig. 3. Percentage of recognition after applying acceptance rate.

In the next steps, we analyzed the length of time required to train and run for each approach. The timing outcomes were achieved in a controlled environment. The outcomes were compiled on a computer processor 11th Gen Intel Core i7 at 2.80GHz speed with installed RAM 16.0 GB. The computer running Windows 11 Pro version 21H2 64-bit operating system and MATLAB R2022a.

The typical running times, which were determined as the average of 30 runs for each database user, are all relatively brief, as shown in Figure 4. In considerably shorter time than half second, they can all conduct real-time recognition. Our solution takes longer to execute due to running PCA and CNN, but only by a set amount of time.

Figure 5 shows the average training time of the three methods. PCA is by far the speediest method as it focuses on using eigenface not on training. The CNN method has the longest training time which is double the training time of the proposed method. The core process in CNN is training the extracted features which are reduced using the PCA in the proposed method.

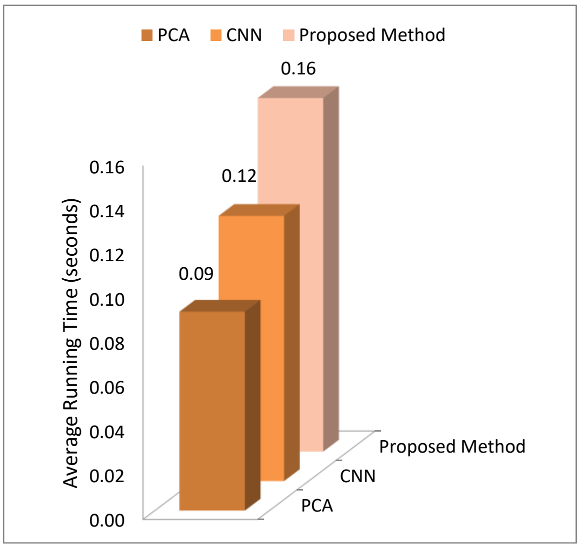

Fig. 4. Average Running Time of the three methods.

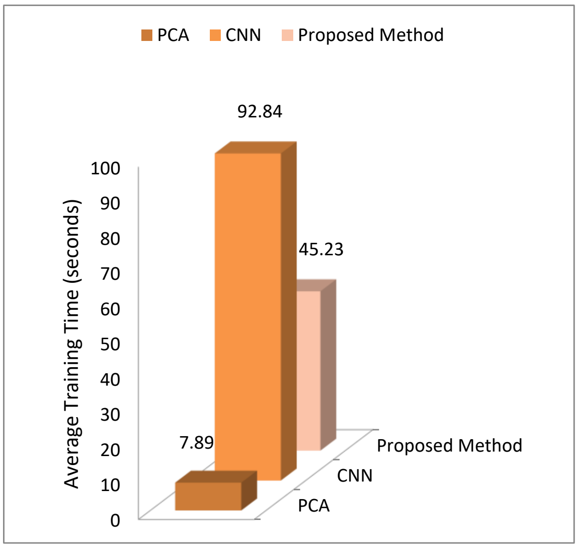

Fig. 5. Average Training Time of the three methods.

5. Conclusion

Facial identification is becoming increasingly important and productive in various applications, such as biometric identification, social media, video surveillance, access control, and content-based data retrieval. Face recognition is more user independent and functions more quickly than other biometric systems. Over the past ten years, deep learning has significantly outperformed conventional computer vision systems thanks to the development of massive data and graphical computing. In this line, we have developed a CNN-based face recognition system that automatically extracts facial features from faces identified by a face detector. The outcomes of the experiments appear that the proposed method is capable of a best recognition rate compared with PCA and CNN to be utilized in facial authentication-based security frameworks.

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References

[1] Rama and F. Tarres, "Lophoscopic PCA: A Novel Method For Face Recognition", Technical report, Departament Teoria del Senyal i Comunicacions de la Universitat Politcnica de Catalunya (UPC), 2005.

[2] King and L. Xu, "Localized Principal Component Analysis Learning for Face Feature Extraction and Recognition", In Proceedings to the Workshop on 3D Computer Vision, pp. 124–128, 1997.

[3] F. Y. Shih and C. Chuang, "Automatic extraction of head and face boundaries and facial features", Information Sciences, 158: pp. 117 – 130, 2004.

[4] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, "Face Recognition: A Hybrid Neural Network Approach", Technical report, University of Mary-land, August 1996.

[5] Tume-Bruce, B. A. A. ., A. . Delgado, and E. L. . Huamaní. "Implementation of a Web System for the Improvement in Sales and in the Application of Digital Marketing in the Company Selcom". International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 5, May 2022, pp. 48-59, doi:10.17762/ijritcc.v10i5.5553.

[6] M. Tamilselvi and S. Karthikeyan, "A Literature Survey in Face Recognition Techniques", International Journal of Pure and Applied Mathematics, Vol. 118, No. 16, pp. 831-849, 2018.

[7] M. Tamilselvi, S. Karthikeyan, & G. Ramkumar, "Face recognition based on spatial angular using visual geometric group-19 convolutional neural network", Annals of the Romanian Society for Cell Biology, pp. 2131-2138, 2021.

[8] S. Poltoratski, K. Kay, D. Finzi, & K. Grill-Spector, "Holistic face recognition is an emergent phenomenon of spatial processing in face-selective regions", Nature communications, vol.12, no.1, pp. 1-13, 2021.

[9] S. Gupta, K. Thakur, & M. Kumar, "2D-human face recognition using SIFT and SURF descriptors of face's feature regions", The Visual Computer, vol.37, no.1, pp. 447-456, 2021.

[10] M. Zulfiqar, F. Syed, M. J. Khan, and K. Khurshid, "Deep Face Recognition for Biometric Authentication", 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), pp. 349-354, 2019, DOI:10.1109/icecce47252.2019.8940725

[11] K. Raju, B. Chinna Rao, K. Saikumar, & N. Lakshman Pratap, "An Optimal Hybrid Solution to Local and Global Facial Recognition Through Machine Learning", In A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems, pp. 203-226, Springer, Cham, 2022.

[12] A. Eleyan, "Simple and Novel Approach for Image Representation with Application to Face Recognition", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), vol.5, no.3, pp. 89-93, 2017.

[13] M. T. H. Fuad, A. A. Fime, D. Sikder, M. A. R. Iftee, J. Rabbi, M. S. Al-Rakhami,... & M. N. Islam, "Recent advances in deep learning techniques for face recognition", IEEE Access, vol.9, pp. 99112-99142, 2021.

[14] F. A. Albalooshi, M. Smith-Creasey, Y. Albastaki, M. Rajarajan, "Facial Recognition System for Secured Mobile Banking" in Sustainability and Resilience Conference: Mitigating Risks and Emergency Planning, KnE Engineering, pp. 92–101, 2018. DOI 10.18502/keg.v3i7.3074

[15] Joy, P., Thanka, R., & Edwin, B. (2022). Smart Self-Pollination for Future Agricultural-A Computational Structure for Micro Air Vehicles with Man-Made and Artificial Intelligence. International Journal of Intelligent Systems and Applications in Engineering, 10(2), 170–174. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/1743

[16] M. S. Kabisha, K. A. Rahim, M. Khaliluzzaman, and S. I. Khan, "Face and Hand Gesture Recognition Based Person Identification System using Convolutional Neural Network", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), vol.10, no.1, pp. 105–115, 2022.

[17] A. Alesmaeil and E. Sehirli, "Detecting Face-Touch Hand Moves Using Smartwatch Inertial Sensors and Convolutional Neural Networks", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), vol.10, no.1, pp. 122–128, 2022.

[18] Ahmed Cherif Megri, Sameer Hamoush, Ismail Zayd Megri, Yao Yu. (2021). Advanced Manufacturing Online STEM Education Pipeline for Early-College and High School Students. Journal of Online Engineering Education, 12(2), 01–06. Retrieved from http://onlineengineeringeducation.com/index.php/joee/article/view/47

[19] Agarwal, D. A. . (2022). Advancing Privacy and Security of Internet of Things to Find Integrated Solutions. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 05–08. https://doi.org/10.17762/ijfrcsce.v8i2.2067

[20] M. Turk and A. Pentland, "Eigenfaces for Recognition", Journal of Cognitive Neuroscience, vol.3, no.1, pp. 71–86, 1991.