

PERFORMANCE EVALUATION OF BLOCK-SIZED ALGORITHMS FOR MAJORITY VOTE IN FACIAL RECOGNITION

Andrea Ruiz-Hernandez , Jennifer Lee, Nawal Rehman, Jayanthi Raghavan
and Majid Ahmadi

Department of Electrical and Computer Engineering, University of Windsor,
Windsor, Canada.

ABSTRACT

Facial recognition (FR) is a pattern recognition problem, in which images can be considered as a matrix of pixels. There are many challenges that affect the performance of face recognition including illumination variation, occlusion, and blurring. In this paper, a few preprocessing techniques are suggested to handle the illumination variations problem. Also, other phases of face recognition problems like feature extraction and classification are discussed. Preprocessing techniques like Histogram Equalization (HE), Gamma Intensity Correction (GIC), and Regional Histogram Equalization (RHE) are tested in the AT&T database. For feature extraction, methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), and Local Binary Pattern (LBP) are applied. Support Vector Machine (SVM) is used as the classifier. Both holistic and block-based methods are tested using the AT&T database. For twelve different combinations of preprocessing, feature extraction, and classification methods, experiments involving various block sizes are conducted to assess the computation performance and recognition accuracy for the AT&T dataset. Using the block-based method, 100% accuracy is achieved with the combination of GIC preprocessing, LDA feature extraction, and SVM classification using 2x2 block-sizing while the holistic method yields the maximum accuracy of 93.5%. The block-sized algorithm performs better than the holistic approach under poor lighting conditions. SVM Radial Basis Function performs extremely well on the AT&T dataset for both holistic and block-based approaches.

KEYWORDS

Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA).

1. INTRODUCTION

Biometric recognition includes various techniques like fingertips, face recognition, and iris methods. Except FR, other methods demand an individual's involvement to access the system. Among such methods, face recognition is a powerful technique that can be carried out in a covert manner [6]. FR has undergone significant advancements in recent years and has been widely implemented in various applications including access control systems, driving licenses [2], passport authentication, smartphones, public safety [3] criminal identification [1], and network security [4]. However, the performance of face recognition is affected by many factors like occlusion, aging, similar faces, expression variation, and resolution [5]. These poor conditions significantly impact the facial recognition system resulting in inaccurate identification. Face images are often affected by illumination variation. Even with the best face recognition systems, the recognition accuracy may be affected by illumination variation [17].

Image preprocessing is a technique to convert raw image information into perfect data, as the raw image may have noisy, incomplete, and/or unpredictable values [15]. There are many preprocessing algorithms available in the literature to improve the captured image in turn boosting the recognition rate. Some popular techniques include but are not limited to Image normalization, de-noising, HistogramEqualization, image resizing, and cropping. Image preprocessing is performed before the feature extraction phase [16].

Feature extraction is one of the important phases of face recognition. Numerous feature extraction methods are applied to extract features of facial images [18]. Some of the extensively applied feature analysis methods are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Binary Pattern (LBP), and Independent Component Analysis (ICA).

The output of the feature extractor is fed as the input to the classifier. Facial images are classified by applying a wide range of classifiers to the respective classes of faces [19]. A few examples of popular classifiers are Random Forest (RF), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM)

2. RELATED WORK

In recent times, automatic face recognition systems obtained the highest accuracy in uncontrolled environments. Yet, there are challenges that need to be addressed in uncontrolled environments [20]. Illumination variation is one of the great challenges that must be handled properly to achieve higher accuracy in the FR system. Various approaches have been recommended to resolve this problem. In this paper, a few preprocessing methods to handle the illumination variation problem are suggested [20].

Histogram Equalization (HE) is one of the widely applied normalization methods in preprocessing. Equalizing a histogram is to extend and reorganize the original histogram using the whole range of discrete levels of the image [10]. The histogram equalization does not work well when there is a non-uniform illumination variation.

For the image $I(x, y)$ with discrete k gray values, histogram is defined by the probability of occurrence of the gray level I [27], given by Equation (1) as follows:

$$P(i) = n_i / N \quad (1)$$

Where $i \in 0, 1 \dots k - 1$ gray level and N is total number of pixels in the image.

HE is applied to the entire image and RHE is performed on smaller regions within the image. The image is divided into regions and histogram equalization is applied separately to each region. This method enhances each region's contrast independently [8], which preserves the details and prevents noise that can occur with global HE

Another type of HE recommended in literature is namely Contrast Limited Adaptive Histogram Equalization (CLAHE), which works extremely well under local lighting varieties [9].

GIC is a preprocessing technique that can be applied to control the overall brightness of the image. It is a nonlinear approach shown in Fig.1. While usual image normalization techniques like scalar multiplication and addition/subtraction perform linear operations on individual pixels [13], GIC [12] shown in Fig. 1 is applied to correct the differences between the content captured by the camera the manner in which the display device displays, content and the way the human visual

system handles light. GIC transforms gray-level I to gray-level $I^{1/\gamma}$ and is given by the following equation (2). But Gamma Correction does not eliminate problems like shading effects [10].

$$I = I^{1/\gamma} \quad (2)$$

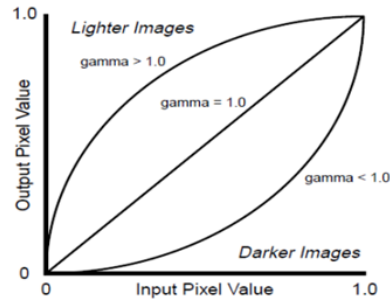


Figure 1. Gamma Intensity Correction

The adaptive Gamma correction method was recommended [14] to overcome the limitations of simple gamma correction. It partitions the value of the gray-scale image into three parts: highlights, transition, and shadow, and then creates the nonlinear association between the gray-scale value and the Gamma value.

The feature extraction process is the next step in face recognition. By applying the LBP operator, the features of the image are extracted by partitioning into small areas called blocks and then the binary pattern histograms are extracted [11]. T. Ojala et al. [7] introduced the original LBP, which is a powerful extractor to represent image texture.

Not all the features extracted from feature extraction are useful data. To process the huge extracted data effectively, its dimensionality must be decreased. Basically, dimensionality reduction converts data with higher dimensionality to a lower dimensionality through a linear transformation. Principle component Analysis (PCA) is the best example of a dimensionality reduction technique. The reduced meaningful data representation must have a dimensionality that corresponds to the intrinsic dimensionality of the data [29]. The intrinsic dimensionality of data represents the number of variables needed in a minimal representation of the data [30].

During the conversion, most representative data is kept and the noisy, redundant data is removed. Because of this feature, PCA is extensively applied as a dimensionality reduction tool in face recognition systems [24]. In this paper, the optimal number of features required for each feature extraction method to get the highest accuracy is discussed.

Linear Discriminant Analysis (LDA) explicitly aims to model the difference between the data of various classes. LDA performs extremely well in face recognition applications, by decreasing the intra-class variation that occurs between individuals in the same class due to illumination variation and increasing the inter-class variation in appearance due to differences in identity [25]. Independent Component Analysis (ICA) is a general form of PCA [25]. PCA optimizes second-order data, which is the covariance matrix. But ICA optimizes higher-order data like kurtosis. For face recognition applications, it is necessary to understand the higher-order relationship between the pixels. ICA performs better than PCA in FR [26].

SVMs fall under the category of maximum margin classifiers. SVM carries out classification between two classes by detecting a decision margin that has the greatest distance to the nearest

points in the training set which are known as support vectors [31]. SVMs are effective binary classifiers that search the feature space for a decision hyperplane that maximizes the difference between two classes (-1 and 1) [21][22][23]. Although SVM handles non-linearly separable data using kernel functions, SVMs are most successful when the data is linearly separable. However, SVMs can be computationally intensive when working with large datasets and non-linear functions.

Hongshuai Zhang et al [32] recommended a face recognition model that makes use of the LBP feature and CNN. LBP is applied to transform the image to a feature map, then the LBP feature map is applied to CNN as the input train CNN. The recommended combination of LBP and CNN performed better in terms of accuracy, sensitivity, and specificity compared to applying CNN alone.

Dadi, Harihara Santosh, and others suggested a face recognition method, in which the Histogram of Oriented Gradient is applied as a feature extractor and SVM as a classifier [33]. Extracted features from HOG are fed to the Support Vector Machine classifier. The system achieved a good accuracy of 92% in the Yale database

3. EXPERIMENT

Experiments are conducted in the AT&T database, which consist of 400 images [28] shown in Fig.2 using the holistic and block-based methods. In this experiment, 80% of the data was used for training and the remaining 20% for testing. Experiments are conducted to find the optimal number of features that would result in the highest accuracy rate and the best parameter values for various preprocessing techniques.



Figure 2. Sample Images from AT&T database.

3.1. Holistic Method

The holistic method shown in Fig.3 accepts the entire facial image as the input. In this method, the preprocessing methods are applied to the complete image. Then the image is block sized.

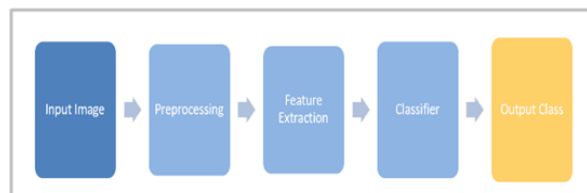


Figure 3. Implementation of the holistic approach

HE, GIC, and RHE are commonly used methods to enhance image quality before features are extracted. In HE, the overall illumination and visibility of details in an image are enhanced. This is achieved by redistributing the intensity value across the entire range. In the given dataset, the intensity values range from 0 to 255, which represents the pixel's illumination. The first stage in HE is to plot the histogram of the image, which is the frequency of each intensity value. Then, the Cumulative Distribution Function (CDF) of the histogram was calculated. The CDF is the probability of each intensity value occurring in the given image. After, the CDF was normalized to cover the intensity values ranging from 0 to 255, and a mapping function was created. Then, new intensity values were assigned to the original input image based on the mapping function.

GIC was applied to the input images. The overall brightness of the image can be controlled by the gamma value (γ). When γ is less than 1, the image appears brighter because the low-intensity values are heightened. In contrast, when γ is greater than 1, the image appears darker as higher intensity values are amplified. The three gamma values, 0.7, 1.5, and 2.2, were tested and the results are given in Table 5.

For feature extraction PCA, LDA, ICA, and LBP methods are applied. Using PCA, the data points with the greatest variance are extracted, which also contain the most useful information. This reduces the computational burden significantly and eliminates any redundancy of features. When the number of feature vectors increases, the computational burden also increases but it gives more accuracy.

The other hyperparameters, namely the kernel (Radial Basis Function (RBF) in this case) and gamma were found through the trial-and-error method. To decide the best kernel, all the basic kernel functions like Linear, Polynomial, and Radial Basis Functions (RBF) are tested. Based on the results, RBF is chosen as the best kernel function for all cases. To find the best gamma value, an arbitrary value was set first, and from multiple trial-and-error iterations, the best gamma value which gave the best performance for each case was found. The parameters used for the Holistic method for all the preprocessing methods like HE, GIC, and RHE are given below in Table 1. The accuracy rates are given in Table 2

SVM is applied as a classifier in this experiment. SVMs are binary classifiers meant to optimally separate two sets of data by using straight lines. There are two general approaches to finding the optimal hyperplane, the first being a maximum-margin hyperplane, in which the aim is to place the hyperplane "in the middle" of both data clusters to maximize the distance from the hyperplane to both clusters [15]. A soft margin differs in that it allows for some misclassifications to account for anomalous data points [15]. The number of misclassifications allowed is generally tuned using the hyperparameter C. This type of margin was selected for the SVM used in this experiment as indicated in the last column of Table 1.

Table 1: Parameters for classification using the whole image

Preprocessing	Feature Extraction	Kernel	Gamma	C
HE	LDA	RBF	35	1
HE	PCA	RBF	15	1
HE	LBP	RBF	0.007	1
HE	ICA	RBF	15	1
GIC	LDA	RBF	35	1
GIC	PCA	RBF	15	1
GIC	LBP	RBF	0.05	1
GIC	ICA	RBF	15	1
RHE (4x4)	LDA	RBF	15	1
RHE (4x4)	PCA	RBF	20	1
RHE (4x4)	LBP	RBF	0.007	1
RHE (4x4)	ICA	RBF	10	1
RHE (4x4)	PCA		85.5	
RHE (4x4)	LBP		76.5	
RHE (4x4)	ICA		90.75	

Table 2: Accuracy results for facial recognition using whole image for classification (holistic approach)

Preprocessing	Feature Extraction	Accuracy (%)
HE	LDA	86.5
HE	PCA	90
HE	LBP	73
HE	ICA	90
GIC	LDA	91.75
GIC	PCA	93.5
GIC	LBP	79.25
GIC	ICA	93.25
RHE (4x4)	LDA	71.75

3.2. Block-Based Method

It is difficult to achieve higher accuracy using a holistic approach, as it is affected by illumination variation. The block-based method shown in Fig.4 is different from the holistic approach, as the input image was divided into smaller sub-images/blocks and each sub-image was processed separately. The separate blocks would be recombined at the end with their classifier scores summed up to determine the class of the input image. The general steps for the block-sizing approach are given as follows.

A specialized preprocessing technique called RHE is applied in the block-based method. It is an extension of the traditional histogram equalization that applies to local regions of the image.

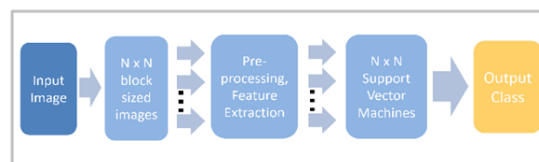


Figure 4.Implementation of Block-sized Method

Instead of implementing HE globally to the entire image, RHE is performed on smaller regions within the image. The image is divided into N-by-N non-overlapping regions and histogram equalization is applied separately to each region. This method enhances each region's contrast independently, which preserves the details and prevents over-amplification of noise that can occur with global HE. The number of blocks (N-by-N) is a variable parameter. The experiment is conducted for 2x2, 4x4, and 8x8 block sizes, and the accuracies are tested for each block size given in Table 6.

For the GIC preprocessing technique, the most optimal gamma value was assigned to each block, depending on the mean pixel intensity. Three gamma correction factors with the values 1.8 (low), 1.5 (medium), and 2.2 (high) are chosen based on the measured brightness of the region by trial-and-error method.

In the block-sized approach, feature extraction was applied to each block as an individual image. The optimal number of features necessary to achieve the highest accuracy is the same for both holistic and block-sized methods. Results are given in Table 3. Support Vector Machine (SVM) is applied as a classifier for block-sized methods also. Parameters for classifying different values of Regional Histogram Equalization (RHE) for different block sizes is given in Table 4. Optimal Parameters for preprocessing for both Holistic and Block-sized Approaches are given in Table 5. Accuracy rates of the block-sized approach for various block sizes are given in Table 6. Parameters for classification using the block-sized approach are given in Table 7.

Table 3: Parameters for feature extraction for both Holistic and Block-sized Approaches

Method	Number of Components
Linear Discriminant Analysis (LDA)	4
Principal Component Analysis (PCA)	9
Local Binary Pattern (LBP)	8 (neighbor pixels)
Independent Component Analysis (ICA)	12

The performances of different block sizes for RHE for each feature extraction method are evaluated. The final parameters used in those tests are shown in Table 4

Table 4: Parameters for classifying different values of RHE block sizes

RHE Block Size	Feature Extraction	Gamma
2x2	LDA	20
2x2	PCA	10
2x2	LBP	0.007
2x2	ICA	10
4x4	LDA	15
4x4	PCA	20
4x4	LBP	0.007
4x4	ICA	10
8x8	LDA	12
8x8	PCA	10
8x8	LBP	0.007
8x8	ICA	10

Table 5: Parameters for preprocessing for both Holistic and Block-sized Approaches

Method	Parameter
Regional Histogram Equalization (RHE)	Block Size = 4
Gamma Intensity Correction (GIC)	Gamma = 2.2 (holistic) Gamma = 1.2, 1.5, 1.8 (block-sized)

Table 6: Accuracy results for facial recognition using the block sizing approach for classification using 2x2, 4x4, and 8x8 block sizes

Preprocessing	Feature Extraction	Accuracy (%)		
		2x2	4x4	8x8
HE	LDA	98.25	100	100
HE	PCA	95.75	97.25	96
HE	ICA	93.75	94	93.25
GIC	LDA	100	100	100
GIC	PCA	95	97.25	95.25
GIC	ICA	94	96.5	994.5

Table 7: Parameters for classification using the block-sized approach

Preprocessing	Feature Extraction	Gamma		
		2x2	4x4	8x8
HE	LDA	10	10	35
HE	PCA	10	10	15
HE	ICA	10	10	15
GIC	LDA	15	15	20
GIC	PCA	15	25	20
GIC	ICA	10	30	15

The performances of different block sizes for RHE using the holistic approach were also evaluated and given in Table 8

Table 8: Accuracy results using different block sizes of RHE for the whole image classification

RHE Block Size	Feature Extraction	Accuracy (%)
2x2	LDA	85
2x2	PCA	85
2x2	LBP	75.75
2x2	ICA	88.75
4x4	LDA	71.75
4x4	PCA	85
4x4	LBP	76.5
4x4	ICA	90.75
8x8	LDA	63.75
8x8	PCA	75
8x8	LBP	78.25
8x8	ICA	78.75

4. CONCLUSIONS

In this paper, both the holistic approach and block-based approach are examined to accurately and efficiently recognize individuals under poor lighting conditions. The experiments are conducted for twelve different combinations of preprocessing, feature extraction, and classification methods. Extensive experiments were carried out for block-based methods with different block sizes to assess the computation performance and recognition accuracy for the AT&T dataset. Another aspect of the research was combining multiple preprocessing techniques on both the entire image, as well as the blocks of an image to evaluate how the performance is affected. The goal was to find the facial recognition model that performed better than the others and remained less of a computational burden.

The combination with a success rate of 100% was achieved using GIC preprocessing along with LDA feature extraction and SVM classification, with 2x2 block-sizing. For this combination, all individuals were successfully recognized by the trained model. Furthermore, the 2x2 block-sizing has a shorter runtime than any other block size, combined with the faster computation of GIC, LDA, and SVM

PCA may not be the most optimal choice as a feature extraction method for a dataset that contains illumination variation. LDA is often used and preferred because of its simplicity and accuracy.

Experimental results prove that Radial Basis Function (RBF) kernel SVMs perform best on the AT&T face dataset.

The accuracy rate of the holistic approach is between 80% to 90%. The accuracy rate of the block-sizing approach, which uses the same combinations, is much higher than the holistic approach around 100%. The block-sizing approach performs much better than the holistic approach under poor illumination conditions. In future work, we plan to address other challenges in face recognition like low resolution.

REFERENCES

- [1] Kortli, Y., Jridi, M., Al Falou, A., & Atri, M. (2020). Face recognition systems: A survey. *Sensors*, 20(2), 342.
- [2] Singh, Shilpi, and S. V. A. V. Prasad. "Techniques and challenges of face recognition: A critical review." *Procedia computer science* 143 (2018): 536-543.
- [3] Hu, Yongmei, et al. "The development status and prospects on the face recognition." *2010 4th International Conference on Bioinformatics and Biomedical Engineering*. IEEE, 2010.
- [4] Li, Lixiang, Xiaohui Mu, Siying Li, and Haipeng Peng. "A review of face recognition technology." *IEEE Access* 8 (2020): 139110-139120.
- [5] Rusia, Mayank Kumar, and Dushyant Kumar Singh. "A comprehensive survey on techniques to handle face identity threats: challenges and opportunities." *Multimedia Tools and Applications* 82, no. 2 (2023): 1669-1748.
- [6] Taskiran, Murat, Nihan Kahraman, and Cigdem Eroglu Erdem. "Face recognition: Past, present and future (a review)." *Digital Signal Processing* 106 (2020): 102809.
- [7] T. Ojala, Pietikinen and M enp , (2002) "Multi resolution gray-scale and rotation invariant texture classification with local binary patterns", *IEEE Transaction on Pattern Analysis and Machine Intelligence*, pp 971-987.
- [8] Musa, Purnawarman, Farid Al Rafi, and MissaLamsani. "A Review: Contrast-Limited Adaptive Histogram Equalization (CLAHE) methods to help the application of face recognition." *2018 third international conference on informatics and computing (ICIC)*. IEEE, 2018.

- [9] R. P. Dahake¹, M. U. Kharat and S.V. Gumaste Comparative Study of Illumination Pre-processing Techniques using Histogram Equalization and its Application in Face Recognition, Biosc.Biotech.Res. Comm. Special Issue Vol 13 No 14 (2020) Pp-394-403
- [10] S. Anila and N. Devarajan, "Preprocessing Technique for Face Recognition Applications under Varying Illumination Conditions Preprocessing Technique for Face Recognition Applications under Varying Illumination Conditions," *Global Journal of Computer Science and Technology Graphics & Vision*, vol. 12, 2012, Available: https://globaljournals.org/GJCST_Volume12/2-Preprocessing-Technique-for-Face-Recognition.pdf
- [11] Rouhi, R., Amiri, M., &Irannejad, B. (2012). A review on feature extraction techniques in face recognition. *Signal & Image Processing*, 3(6), 1.
- [12] Chapter 4 - Digital picture formats and representations David R. Bull, Fan Zhang,in *Telligent Image and video Compression (Second edition) 2021*
- [13] Shabana, D. F., Badithala, S., Daggupati, S., Chevala, R., & Raj, K. (2020). an Image Enhancement Algorithm Using Gamma Correction By Swarm Optimization. *Int Res J Eng Technol*, 7(9).
- [14] Zhang, Xue-Wen, et al. "A Method of Continuous Nonlinear Gamma Correction." *2nd Annual International Conference on Electronics, Electrical Engineering and Information Science (EEEIS 2016)*. Atlantis Press, 2016.
- [15] Chaki, Jyotismita, and Nilanjan Dey. *A beginner's guide to image preprocessing techniques*. CRC Press, 2018.
- [16] Dharavath, Krishna, Fazal Ahmed Talukdar, and Rabul Hussain Laskar. "Improving face recognition rate with image preprocessing." *Indian Journal of Science and Technology* 7.8 (2014): 1170-1175.
- [17] Wei, Pengcheng, et al. "Research on face feature extraction based on K-mean algorithm." *EURASIP Journal on Image and Video Processing* 2018.1 (2018): 1-9.
- [18] WW Bledsoe, The model method in facial recognition, vol 15 (Panoramic Research Inc, Palo Alto, 1966), p. 47
- [19] Dino, H. I., & Abdulrazzaq, M. B. (2019, April). Facial expression classification based on SVM, KNN and MLP classifiers. In *2019 International Conference on Advanced Science and Engineering (ICOASE)* (pp. 70-75). IEEE.
- [20] L. Zhichao and E. M. Joo, "Face Recognition under Varying Illumination," *New Trends in Technologies: Control, Management, Computational Intelligence and Network Systems*, 2010.
- [21] D. Xi, I. T. Podolak, and S.-W. Lee, "Facial component extraction and face recognition with support vector machines," *Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition*, 2002.
- [22] Guodong Guo, S. Z. Li, and Kapluk Chan, "Face recognition by support Vector Machines," *Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition (Cat. No. PR00580)*.
- [23] M. O. Faruque and M. A. Hasan, "Face recognition using PCA and SVM," *2009 3rd International Conference on Anti-counterfeiting, Security, and Identification in Communication*, 2009.
- [24] Peng, P., Portugal, I., Alencar, P. and Cowan, D., 2021. A face recognition software framework based on principal component analysis. *Plos one*, 16(7), p.e0254965.
- [25] Bhattacharyya, S. K., & Rahul, K. (2013). Face recognition by linear discriminant analysis. *International Journal of Communication Network Security*, 2(2), 31-35.
- [26] Stone, J. V. (2002). Independent component analysis: an introduction. *Trends in cognitive sciences*, 6(2), 59-64.
- [27] Raghavan, Jayanthi, and Majid Ahmadi. "Performance Evaluation of Weighted Entropy Based Fusion Technique for Face Recognition with Different Pre-processing Techniques." *Advances in Information and Communication: Proceedings of the 2021 Future of Information and Communication Conference (FICC), Volume 2*. Springer International Publishing, 2021.
- [28] "The Database of 31a GTDLBench, [https://gitdisl.github.io/GTDLBench/datasets/att_face_dataset/#:~:text=The%20AT%26T%20face%20dataset%2C%20E%2080%9C,\(April%201994%20at%20the%20lab.](https://gitdisl.github.io/GTDLBench/datasets/att_face_dataset/#:~:text=The%20AT%26T%20face%20dataset%2C%20E%2080%9C,(April%201994%20at%20the%20lab.) (accessed Jul. 31, 2023).
- [29] Van Der Maaten, Laurens, Eric O. Postma, and H. Jaap van den Herik. "Dimensionality reduction: A comparative review." *Journal of Machine Learning Research* 10.66-71 (2009): 13.
- [30] K. Fukunaga. *Introduction to Statistical Pattern Recognition*. Academic Press Professional, Inc., San Diego, CA, USA, 1990.

- [31] Heisele, Bernd, Purdy Ho, and Tomaso Poggio. "Face recognition with support vector machines: Global versus component-based approach." In *Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001*, vol. 2, pp. 688-694. IEEE, 2001.
- [32] Zhang, Hongshuai, Zhiyi Qu, Liping Yuan, and Gang Li. "A face recognition method based on LBP feature for CNN." In *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, pp. 544-547. IEEE, 2017.
- [33] Dadi, Harihara Santosh, and GK Mohan Pillutla. "Improved face recognition rate using HOG features and SVM classifier." *IOSR Journal of Electronics and Communication Engineering* 11, no. 4 (2016): 34-44.