Contents lists available at ScienceDirect

Computer Vision and Image Understanding

journal homepage: www.elsevier.com/locate/cviu

Comparative Analysis of Face Recognition Methods Based on Machine Learning.*

Vrushaket Chaudhari
PICT, Pune
Maharashtra India
vrushu00@gmail.com

Tanvesh Chavan
PICT, Pune
Maharashtra India
tanveshchavan2000@gmail.com

Rushikesh Chaudhari
PICT, Pune
Maharashtra India
rushikeshchoudhari2001@gmail.com

Shantanu Jain
PICT, Pune
Maharashtra India
shantanujain18@gmail.com

Prof. Priyanka Shahane
PICT, Pune
Maharashtra India
psshahane@pict.edu

Abstract

Face recognition is crucial for identity verification. Face recognition technology has evolved significantly in terms of precision while retaining its usefulness. Face recognition is used for a variety of identity verification applications, including presence and security monitoring. While the demand for computer vision applications has increased and included identifying numerous persons in a crowded environment, the technologies for face recognition that are now available mostly are only for short-range and single-face situations. Therefore, to overcome this problem, the best strategy must be chosen. This study proposes handcrafted descriptors such as Haar Cascade, PCA(Principal Component Analysis), SVM(Support Vector Machine), LDA(Linear Discriminant Analysis) LBP(Local Binary Patterns), and HOG (Histogram of Gradient) for extracting image features..

Keywords: Face-recognition, computer vision, principal component, short-range, descriptors

1. Introduction

It is currently difficult to automatically track and locate an individual using facial detection and identification in an unrestricted massive crowd gathering. Because of a variety of dynamic aspects, including low resolution, variable crowd distance from installed cameras, portable webcams, and the crowd, face detection, and person identification can be complicated.
Several ideas in the literature use facial recognition methods on photos of massive crowds, including [1,2,3,4], however, it is uncommon to follow a person in a large crowd using low-resolution photos. Recent deep learning

Please cite this article as: First author et al., Article title, Computer Vision and Image Understanding (2017), http://dx.doi.org/10.1016/j.cviu.2017.00.000

methods are utilized for face identification on high-quality photos like [5], however, our analysis of similar work suggests that they underperform on low-resolution photographs of the uncontrolled environment. To the best of our knowledge, the methods utilized in this research have been the first to divide the monitoring area into geofences and estimate a set of geofences for the potential presence of a potential suspect.

Given the recent rise in demand for security monitoring, face recognition merits further development.

Face recognition is considered one of the most useful identity verification methods because of its contact-free capability.

Face recognition algorithms should be deployed on camera systems in various locations for reasons other than security, such as consumer analysis, pedestrian recognition, music event attendance, school attendance, and many other human activities that occur in crowded areas. Therefore, an algorithm must be developed for facial recognition to function well in those crowded places. The algorithm used to identify a person's face in a crowd will vary from that used to identify a human face in a non-crowded environment.

The application of face recognition in many different industries has made it a major area of study in computer vision. If the training data for facial recognition is inaccurate, it can be difficult to If resources are few, face recognition will be less successful. A deep learning technique called Generative Adversarial Networks (GANs) is a technique that can produce high-quality synthetic images.

This work gives a survey of different supervised, semi-supervised, and unsupervised machine learning methods to manage students' attendance at college classes and maintain campus security.

2. Literature Survey

Pattern recognition in machine learning is based on training /learning from a training dataset. This learning can be categorized into three types: supervised, semi-supervised, and unsupervised learning. Labeled data is present at the beginning of the supervised learning class while in semi-supervised learning some of the class labels are known. Whereas, in unsupervised learning, class labels are not available. Once the training phase is finished features are extracted from the data and then a classifier is applied to make predictions for unseen data/objects.

RFID and NFC (Near Field Communication) technology are frequently used in the ID-based attendance checking system. An RFID-based attendance management and information service system called AMS was proposed by Rjeib et al. [7]. Each student's identifying details and class schedule are associated with the student ID card's RFID tag in AMS. The database holds all attendance records and student data, which is then shown on a web application. An NFC-based attendance monitoring system called TouchIn was developed by Ahmad et al. [8]. The reader unit and the web server unit were TouchIn's two major components. Students can mark their attendance by touching the NFC reader with their mobile devices or student ID cards that have NFC tags. The ID-based attendance verification system was upgraded to include one-time password (OTP) technology by Jacob et al. [9]. One-time passwords are randomly generated for each student and sent to their mobile devices once the NFC reader recognizes them as having entered the classroom. To complete the attendance checking process after obtaining the information, the student must enter the password through the pre-installed application on the mobile device. The location-based attendance verification system often makes use of wireless communication (such as Bluetooth and Wi-Fi) communication distance limitations to regulate attendance.

An attendance management system based on Android and Arduino was developed by Cisar et al. [6]. Students upload login information to the Arduino development board through Bluetooth using Android apps. However, it is challenging to restrict the region where attendance is being checked because it is tough to manage the wireless signal's coverage. Abdulkareem et al. incorporated a random forest classifier and near-field positioning technology based on Bluetooth Low Energy (BLE) devices [10] to identify pupils who were inside or outside the classroom. Anand et al. validated a student's identification using a mobile device's camera [11], and they only allowed students to be checked for attendance inside the classroom by using Wi-Fi indoor positioning technology. They employed Wi-Fi fingerprinting technology for indoor locating, and by examining features including device proximity, device movement trajectories, and time sampling, they were able to increase the accuracy of both the RSSI gathering process and the total placement. The location-based attendance checking system can also leverage several data processing technologies that increase human localization accuracy [12], [13].

The biometrics-based attendance monitoring systems often use face, fingerprint, and other biometric technology to identify attendees. An attendance monitoring system based on fingerprint identification was created by Muchtar et al. [14]. Each individual may be recognized on various fingerprint sensors thanks to the usage of Arduino and Raspberry Pi to manage fingerprint data centrally, which boosts the effectiveness of managing attendance.
A deep learning-based face recognition attendance checking system called FaceTime was proposed by Arsenovic et al. [15]. Students should first enter their identity from their ID cards before FaceTime may gather and recognize their faces via the webcam and record their attendance in the classroom, but the system is limited to marking attendance inside the classroom only.
In addition to developing a comparable mobile device application, Yang et al. presented an intelligent attendance verification system based on voiceprint recognition and real-time geographical locating [16]. The application activates the device's microphone during attendance checking, and students finish the process by reading a passage of text. About 120 students from a first-year computer science course participated in the testing of this program. The length of the attendance check can be capped at five minutes if the application satisfies the necessary accuracy requirements.
Using the LBPH algorithm for face recognition and the haar cascade for face detection, Bharath Tej Chinimilli et al. [21] trained a model. To train the model, they used their dataset. This system offers features like photographing students and recording their information for the database, training the photos in the database and on the camera, and beginning to track persons entering the classroom. This system recognizes the faces of students walking into the classroom from the webcam and pre-processes them for further processing.
The following are some downsides of the aforementioned types of attendance verification systems.
(1) The ID-based attendance checking system's cost is high, and it is difficult to verify students' identities;
(2) The location-based attendance checking system can only count the number of mobile devices in the attendance checking area; it is unable to determine the precise number of students who participate in attendance checking.

3. Algorithms

EIGENFACES

Eigenfaces is face detection and recognition technology that determines face variance in image data sets. With the aid of machine learning, it encodes and decodes faces using these variations. A collection of "standardized face constituents" known as a set of eigenfaces is produced by statistically analyzing many different face photos. Since this method doesn't use digital images but rather statistical databases, facial traits are given numerical values. A mixture of these variables in various percentages makes up every human face.[17][19]

FISHERFACES
Fisherfaces is a prominent facial recognition algorithm that is deemed superior to many of its competitors. It is frequently compared to Eigenfaces as a development of that technique and is regarded as more effective at class separation during training. The main benefit of this algorithm is its capacity to extrapolate and interpolate over variations in illumination and face expression. When used in conjunction with the PCA approach during the preprocessing stage, the Fisherfaces algorithm has been reported to have a 93% accuracy rate.[18]

HAAR CASCADES
Haar Cascade is a method for detecting objects in photographs. The algorithm learns from a huge number of positive and negative samples, where a positive sample contains an object of interest and a negative sample contains anything else. The classifier can identify an interesting object on fresh photos after training. Combining the technique with the local binary pattern algorithm was utilized in criminal identification to identify faces. Even with fluctuating expressions, the Haar cascade classifier requires 200 (out of 6000) characteristics to guarantee an 85-95% recognition rate.[19]

LOCAL BINARY PATTERNS HISTOGRAMS (LBPH)

Local binary patterns (LBP), a simple, efficient texture operator in computer vision, are used in this technique to mark individual pixels in an image by setting a neighborhood threshold for each pixel and then treating the result as a binary number. The LBPH method generates histograms for each labeled and classed image during the learning phase. Each image from the training set is represented by a different histogram. In this approach, comparing the histograms of any two photos is what the actual recognition procedure entails.

4. Performance Parameters

The performance depends upon the method of classification and dataset used for classification. The various performance parameters used in the above literature survey are as follows:

F1 score is a combination of precision and recalls it is calculated as, F1 Score: 2*(Precision * Recall / (Precision + Recall)

- Precision can be calculated as,
  Precision: TP / TP + FP
  Where,
  TP (True Positive) test result detects the condition when the condition is present.
  FP (False Positive) test result detects the condition when the condition is absent.

- Recall (Sensitivity/ TP Rate) can be calculated as,
  Recall: TP/ TP + FN
  Where,
  FN (False Negative) test result does not detect the condition when the condition is present.

- Specificity (TN Rate) can be calculated as,
  Specificity: TN/ TN + FP
  Where,
  TN (True Negative) test result does not detect the condition when the condition is absent.

- FP Rate can be calculated as,
  FP Rate: FP/ FP + TN

- Accuracy can be calculated as,
  Accuracy: sum (abs (Expected Output – Actual Output)) / 2

- PR-AUC: Precision-Recall Area Under Curve (PR-AUC) is a statistical value of the area under the precision-recall curve.

- AUROC (AUC): It is an Area Under ROC (Receiver Operating Characteristic) Curve. ROC is created by plotting TP Rate against FP Rate

5. Comparative analysis

An automated facial recognition system's working mode is determined by the field of application upon installation, either authentication (one to one) or identification (one to many). In the first mode, the system must confirm a person's identification by designating him as a genuine user or imposter. While for the second, the system must assign a registered user's identification to that individual or designate him to be unknown. In both modes, the system needs to have a reference database with all the feature vectors (signatures) of the faces of people the system assumes it knows. Enrollment is the step during which these signatures are learned. Furthermore, to identify or authenticate a person from his face image (query face image) in the recognition phase, the same steps have to be taken, but this time around online. These steps provide the following functions:

Extraction of the feature vector:
A face recognition system's extraction of the feature vector is an essential step. This process, which is also known as indexing or modelling, enables the extraction of the facial image and the identification of the relevant data that defines it: feature vector or signature. This vector must vary from person to person and remain constant regardless of the person's changing face features. The literature has a number of feature extraction algorithms.
Classification: At this point, the person's feature vector can be divided into several different groups. To handle it properly, a classification or comparison approach that calculates a similarity or distance score between this feature vector and the reference feature vectors in the database is necessary. This score is then compared to a set judgment threshold to draw a conclusion.

Algorithm	Description	Accuracy
PCA	A popular facial recognition algorithm is principle component analysis. Basically, dimensionality reduction is accomplished using this. Eigenfaces are the primary mathematical elements of the face distribution. Due to the fact that they represent the covariance matrix of the facial pictures, they are also known as eigenvectors.[17][18]	89.4
LDA	Before the classification procedure, the number of features is reduced to a more manageable quantity using linear discriminant analysis (LDA). A linear combination of pixel values that creates a template is used to create each of the additional dimensions that are created[18].	91.25
ICA	In certain ways, the recently created statistical method known as independent component analysis (ICA) is superior to PCA. Blind source separation and blind convolution are its main applications.	88.43
PCA + SVM	As a discriminating classifier, a Support Vector Machine (SVM) is officially defined by a different hyperplane. The algorithm that classifies brand-new cases generates an ideal hyperplane given the labeled training data. By creating an N-dimensional hyperplane that splits data into two groups in the best possible way, a Support Vector Machine (SVM) accomplishes classification. This is a combination of both PCA as well as SVM used for classification.	93.12
PCA+ LDA	combination of both PCA as well as LDA used for classification.	95.31

Table 5.1 Face Recognition algorithms and their accuracy

Detection (D)/Recognition Algorithms for Machine Learning (R)	**Data for Unclear Images**	**Huge Crowd Environment**	**Identification and Recognition for Person Tracking**	**Facial recognition and detection algorithms combined**
FaceNet+SVM (D)/ YOLO v3 (R)	Yes	Yes	No	No
Viola Jones(D)/ PCA, DCT, LGBP, LBP, ASR+ (R)	Yes	Yes	No	Yes

LBP(RH)	Yes	Yes	No	No
Well known algorithms for (D) & (R)	Yes	Yes	No	No
CNN (D) / YOLO v4 (R)	No	Yes	Yes	No
PCA, CNN (D) / DT, RF, KNN, CNN (R)	No	Yes	Yes	No

Table 5.2 Facial Recognition Algorithms and their functionality in a crowded environment and in unclear photos

6. Conclusion and Future Directions

From this survey, we found out that many algorithms such as Haar Cascade, PCA, LDA, Eigenfaces, SVM, and ICA have been used to recognize and identify faces from crowds and generate results up to 90%. Also, we found out that after integrating 2 or more algorithms, accuracy increases up to 95%. The performance may decrease based on the environment such as the darkness of the environment, weather conditions, distance, identical faces, etc. Furthermore, the performance can be increased by applying dilation or normalizing the image according to environmental conditions.
Face detection in low-resolution photos is difficult due to limited pixels and inevitable noise, which makes the task much more difficult. A natural answer is to take inspiration from multi-exposure, which takes many pictures to produce well-exposed photographs in difficult lighting situations. However, it is not simple to implement or approximate multi-exposure from a single image in a high-quality manner. To overcome this issue use of a Recurrent Exposure Generation (REG) module and a Multi-Exposure Detection (MED) module can considerably increase face detection performance. By successfully preventing non-uniform illumination and noise problems.

An approach that will get the best results for detecting faces with dark skin is needed because face recognition algorithms struggle to detect faces with dark skin. A hybrid approach that combines the Explicit Rule Algorithm and Gaussian Model to identify faces with dark skin. For face detection in this hybrid system, morphological and anthropological methodologies have been combined.

Occlusion, which is defined as a blockage, happens when one or more facial features are obscured and the entire face is not available for input. One of the biggest problems with facial recognition systems is occlusion.
It is common in real-world situations and is brought on by beards and accessories (such as goggles, hats, and masks). These elements make the topic diversified, which makes automated facial recognition a challenging problem to solve. Due to a lack of publicly available datasets with actual masked face photos, we constructed simulated masked datasets by applying fake masks to the face images from the CASIA-WebFace dataset for training and well-known face benchmarks for testing.
When a person's head moves or their point of view shifts, the posture of their face changes
. The look of a face can always change due to head movements or different camera angles, which results in intra-class variances and a sharp decline in automated face recognition rates. The true face is harder to distinguish as the rotation degree increases. If the database just has the frontal image of the face, it could lead to inaccurate recognition or no recognition at all.
Another important consideration is the different ways that the same person expresses themself. Human expressions, such as those of happiness, sadness, rage, disgust, fear, and surprise, are notably macro-expressions. Micro expressions are quick changes in the way the face moves that occur unintentionally. To overcome the negative consequences of poor fractalization outcomes, the use of WAPNN is a unique technique for achieving excellent performance on multi-view face recognition.

7. References

[1] Jurevičius, R., Goranin, N., Janulevičius, J., Nugaras, J., Suzdalev, I., & Lapusinskij, A. (2019). Method for real-time face recognition application in unmanned aerial vehicles. Aviation, 23(2), 65-70.

[2] Kramer, R. S., Hardy, S. C., & Ritchie, K. L. (2020). Searching for faces in crowd chokepoint videos. Applied Cognitive Psychology, 34(2), 343-356.

[3] Best-Rowden, L., Bisht, S., Klontz, J. C., & Jain, A. K. (2014, September). Unconstrained face recognition: Establishing baseline human performance via crowdsourcing. In IEEE International Joint Conference on Biometrics (pp. 1-8). IEEE.

[4] Becker, D. V., & Rheem, H. (2020). Searching for a face in the crowd: Pitfalls and unexplored possibilities. Attention, Perception, & Psychophysics, 82(2), 626-636.

[5] Rajnoha, M., Mezina, A., & Burget, R. (2020). Multi-frame labeled faces database: Towards face super-resolution from realistic video sequences. Applied Sciences, 10(20), 7213.

[6] S. M. Cisar, R. Pinter, V. Vojnic, V. Tumbas, and P. Cisar, ''Smartphone application for tracking students' class attendance,'' in Proc. IEEE 14th Int. Symp. Intell. Syst. Informat. (SISY), Subotica, Serbia, Aug. 2016, pp. 227–232.

[7] H. D. Rjeib, N. S. Ali, A. Ai Farawn, B. Al-Sadawi, and H. Alsharqi, ''Attendance and information system using RFID and Web-based application for the academic sector,'' Int. J. Adv. Comput. Sci. Appl., vol. 9, no. 1, pp. 266–274, Jan. 2018

[8] B. I. Ahmad, ''TouchIn: An NFC supported attendance system in a university environment,'' Int. J. Inf. Educ. Technol., vol. 4, no. 5, p. 448, Jan. 2014.

[9] J. Jacob, K. Jha, P. Kotak, and S. Puthran, ''Mobile attendance using near field communication and one-time password,'' in Proc. Int. Conf. Green Comput. Internet Things (ICGCIoT), Noida, India, Oct. 2015, pp. 1298–1303.

[10] A. Abdulkareem, ''The design, development, and evaluation of a smart attendance tracking system using Bluetooth low energy beacons,'' M.S. thesis, Dept. Comput. Eng., Kankaya Univ., Etimesgut, Turkey, 2018.

[11] S. Anand, K. Bijlani, S. Suresh, and P. Praphul, ''Attendance monitoring in the classroom using smartphone & Wi-Fi fingerprinting,'' in Proc. IEEE 8th Int. Conf. Technol. Educ. (T4E), Mumbai, India, Dec. 2016, pp. 62–67.

[12] C. Zhou, Y. Gu, S. He, and Z. Shi, ''A robust and efficient algorithm for coprime array adaptive beamforming,'' IEEE Trans. Veh. Technol., vol. 67, no. 2, pp. 1099–1112, Feb. 2018.

[13] X. Zhou, W. Liang, K. Wang, H. Wang, L. T. Yang, and Q. Jin, ''Deep learning enhanced human activity recognition for Internet of healthcare things,'' IEEE Internet Things J., vol. 7, no. 7, pp. 6429–6438, Jul. 2020.

[14] M. A. Muchtar, Seniman, D. Arisandi, and S. Hasanah, ''Attendance fingerprint identification system using Arduino and single board computer,'' J. Phys., Conf. Ser., vol. 978, Mar. 2018, Art. no. 012060.

[15] M. Arsenovic, S. Sladojevic, A. Anderla, and D. Stefanovic, ''FaceTime— Deep learning based face recognition attendance system,'' in Proc. IEEE 15th Int. Symp. Intell. Syst. Informat. (SISY), Subotica, Serbia, Sep. 2017, pp. 53–58.

[16] S. Yang, Y. Song, H. Ren, and X. Huang, ''An automated student attendance tracking system based on voiceprint and location,'' in Proc. 11th Int. Conf. Comput. Sci. Educ. (ICCSE), Nagoya, Japan, Aug. 2016, pp. 214–219.

[17] V. P. Kshirsagar, M. R. Baviskar, and M. E. Gaikwad, "Face recognition using Eigenfaces," *2011 3rd International Conference on Computer Research and Development*, 2011, pp. 302-306, doi: 10.1109/ICCRD.2011.5764137.

[18] Jing, Xiao-Yuan, Hau-San Wong, and David Zhang. "Face recognition based on 2D Fisherface approach." *Pattern Recognition* 39.4 (2006): 707-710.

[19] Padilla, R., Costa Filho, C. F., & Costa, M. G. F. (2012). Evaluation of haar cascade classifiers designed for face detection. *International Journal of Computer and Information Engineering*, *6*(4), 466-469.

[20] Vu, H. N., Nguyen, M. H., & Pham, C. (2022). Masked face recognition with convolutional neural networks and local binary patterns. *Applied Intelligence*, *52*(5), 5497-5512.

[21] B. Tej Chinimilli, A. T., A. Kotturi, V. Reddy Kaipu, and J. Varma Mandapati, "Face Recognition based Attendance System using Haar Cascade and Local Binary Pattern Histogram Algorithm," 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), 2020, pp. 701-704, doi: 10.1109/ICOEI48184.2020.9143046.

[22] Priyanka Shahane, Deipali Gore "A Survey on Classification Techniques to Determine Fake vs. Real Identities on Social Media Platforms,"IJRDT, 2018..

[23] C. Rong, X. Zhang and Y. Lin, "Feature-Improving Generative Adversarial Network for Face Frontalization," in *IEEE Access*, vol. 8, pp. 68842-68851, 2020, doi: 10.1109/ACCESS.2020.2986079

[24] Hsu CC, Lin CW, Su WT, Cheung G. SiGAN: Siamese Generative Adversarial Network for Identity-Preserving Face Hallucination. IEEE Trans Image Process. 2019 Dec;28(12):6225-6236. doi: 10.1109/TIP.2019.2924554. Epub 2019 Jun 28. PMID: 31265397.

[25] Hu, Cong & Feng, Zhen-Hua & Wu, Xiao-Jun & Kittler, Josef. (2020). Dual Encoder-Decoder Based Generative Adversarial Networks for Disentangled Facial Representation Learning. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3009512.

[26] S. Cen, H. Luo, J. Huang, W. Shi and X. Chen, "Pre-Trained Feature Fusion and Multidomain Identification Generative Adversarial Network for Face Frontalization," in *IEEE Access*, vol. 10, pp. 77872-77882, 2022, doi: 10.1109/ACCESS.2022.3193386.

[27] Li, Jinning & Zhou, Yichen & Ding, Jie & Chen, Cen & Yang, Xulei. (2020). ID Preserving Face Super-Resolution Generative Adversarial Networks. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3011699.

[28] H. Pranoto, Y. Heryadi, H. L. H. S. Warnars and W. Budiharto, "Recent Generative Adversarial Approach in Face Aging and Dataset Review," in *IEEE Access*, vol. 10, pp. 28693-28716, 2022, doi: 10.1109/ACCESS.2022.3157617.

[29] Q. Duan, L. Zhang and X. Gao, "Simultaneous Face Completion and Frontalization via Mask Guided Two-Stage GAN," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 6, pp. 3761-3773, June 2022, doi: 10.1109/TCSVT.2021.3111648.