Role Of Machine Learning Algorithm's In Capturing Student's Attendance

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Abstract: The drastic development of computing technologies has abetted the implementation of Automation in Education (AE) applications. The Automation in Education domain refers to the implementation of a machine supported technologies like Machine Learning (ML), Deep Learning (DL), Convolution Neural Networks (CNN), and Artificial Intelligence (AI) to facilitate the process of teaching the students, taking and maintenance of online attendance, capturing the activities of the students in the classroom, automatic face detection, and recognition, identification of prohibited objects in the classrooms and the most challenging automatic online proctoring of online assessments. In the field of education, attendance management of students is a very crucial task to handle. Many researchers try to attempt this problem. In the current era of machine learning, they have tried to automate this time-demanding task. In the case of the human, each face has unique features. The face recognition algorithm uses this concept and provides the solution. This paper provides a survey of the different ML techniques, which explains the face recognition task, through which one can automate this time-consuming attendance process. We also provide a brief explanation of the recent techniques and their performance comparison.

Keywords: Machine learning, Face recognition, Deep learning, Student attendance, Education, Online attendance

1. Introduction

In the modern era of technology, machine learning algorithms provide efficient solutions to automate daily manual tasks. In the field of education, numerous tasks are needed to be done daily. One of the monotonous tasks is taking class attendance of the student. Since student attendance is playing an important role in course evaluation, it measures student regularity during the course. There is an innately optimistic association between class attendance and student success in the classroom. [1].A number of literature do exist depicting the importance of school input variables, ie. student/teacher ratio, quality of education imparted and amenities provided to the students. Recently scant attention is paid to the student input variable, i.e. student attendance, which has shown drastic evidence that the average level of attendance at school has a positive influence on student performance [35]. Many researchers have tried to address this problem using different machine learning techniques.

An alternate approach for tracking student attendance is to use biometric methods. Biometrics are invasive and necessitate human interaction with a variety of technologies. [2]. Since we are facing the COVID pandemic, the biometric system could become a virus transmission medium from one student to the other. So the contactless system needed to be used to track student attendance. Face recognition algorithm came into the picture to provide the contact-less system, which can be done automatically to detect the students' face and mark attendance according to the system result. Since each person has a unique face feature, the face recognition algorithm took various features as input, and in the case of the attendance management system, it would find students with similar features and mark the student's attendance in the system designed to keep track of the attendance record. The face recognition approach is focused on training a system with a single image of a student to detect, segment, and validate student identities in an unregulated environment (class pictures) [3]. Based on the how and which feature of the face needs to be considered, many machine learning techniques are available. This survey paper is trying to demonstrate the recent techniques and approaches to handle this problem. The paper will contain the basic machine learning techniques to advance deep learning algorithms. Also discussed the performance of each technique on benchmark datasets.

2. Related Work

Qingshan and Rui, in their paper [4] described Fisher Linear Discriminant Analysis (FLDA) and Principal Component Analysis (PCA) usage in the case of face recognition. For handling complex data i.e. illumination, facial expression, and pose variations, they have used the kernel-based FLDA and PCA. After finding the subspace representation of the face images using the kernel, the data is passed through the face recognition methods. It has been observed that the kernel approach of the FLDA and

PCA gives promising results compared to the standard Eigenface, Fisherface, ICA-based, and SVM-based face recognition methods. AT & T and YALE [5] database is used to check the performance of the proposed approach.

Samuel and Aditya, in their paper [6], discussed the Discrete Wavelet Transforms (DWT) and Discrete Cosine Transform (DCT) to extract the features of the student's face. After extracting the feature, Radial Basis Function

(RBF) [7] was used for classifying the facial objects. They have discussed the feature-based and brightness-based approaches for feature extraction. The feature-based approach uses keypoint features of the face such as edges, eyes, nose, mouth, or other special characteristics. In this calculation, only some part of the image is considered, while the brightness-based approach calculates all parts of the given image. If all parts of the images will be considered, then the brightness-based approach computation time increases. In figure 1, the proposed approach is shown.

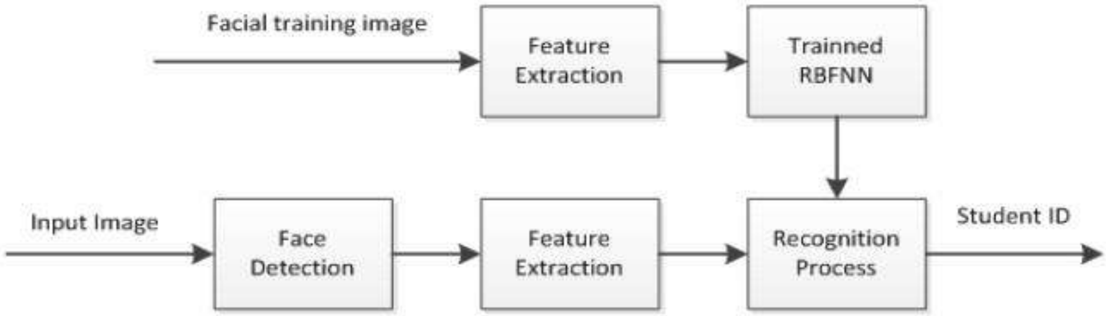


Figure 1: Overall approach [6]

Input is an image of a student, and output is a student ID. Training data is a student's facial image. For testing the performance of the system, 186 student facial images are used, which are created from 16 students. As a part of the pre-processing phase, the gray-scale normalization, histogram equalization, Discrete Wavelet

Transform (DWT), and Discrete Cosine Transform (DCT) is applied to the images, after applying all the pre-processing procedure, images are passed to the Radial Basis Function (Neural) Network (RBFN). They have proved that the success rate of this recognition system is 82%.

P. Wagh, R. Thakare, and their team member in paper [8] has described the PCA and eigenface approach for face recognition. They have compared the different approaches, including the neural network. In Figure, their proposed approach is shown.

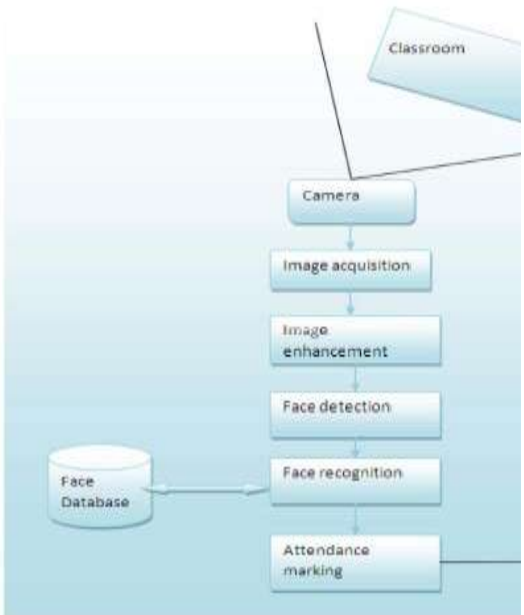


Figure 2: Proposed approach

In the first step, they have collected data of the students, which can be used for matching the face detection result. As a part of the image acquisition, the high definition camera will be used, and after collecting the image, it is converted to a greyscale image. Then several image pre-possessing techniques are applied i.e., histogram normalization, noise removal techniques, and skin classification. As a face detection part, first, need to crop the student face from the images, and the region of interest need to be selected. Eigenface [9] is calculated, and

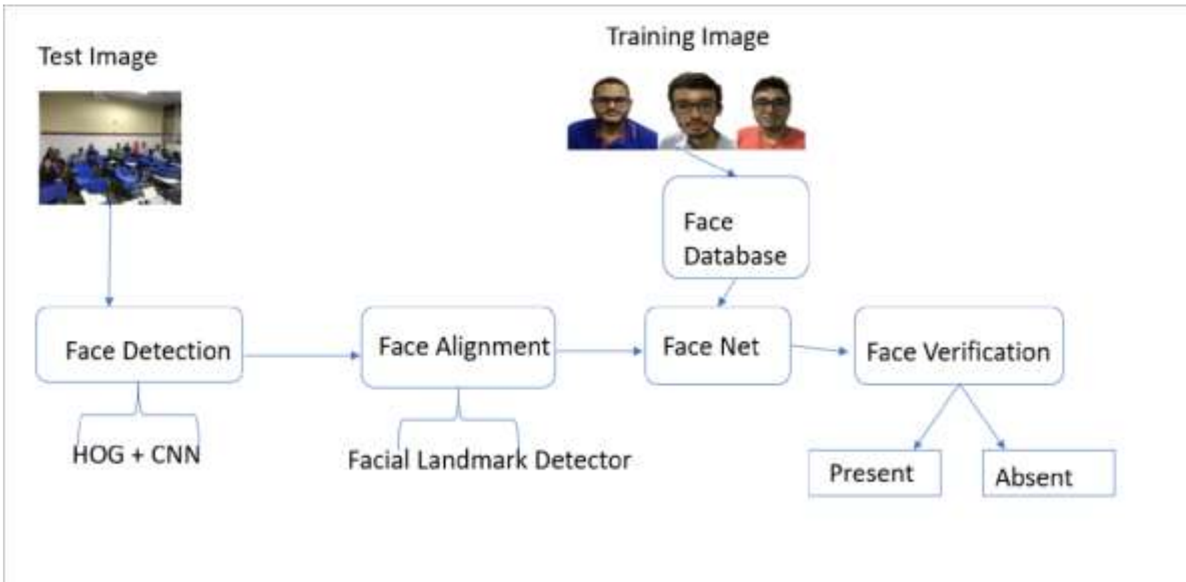
Euclidean distance will be calculated between the image and the eigenfaces. Image is recognized if minimum Euclidean distance is found between the image and eigenface.

In any automatic attendance system, face detection task plays an important role. Peiyun Hu, Deva Ramanan in their paper [10] address the challenges while detecting the small faces in the face detection faces. They have discussed the following three issues during the face detection pre-processing step: the role of scale invariance, image resolution, and contextual reasoning. After the face detection phase, we need to check whether the detected face is present in the database. The face recognition algorithm will help mark students' attendance whose data is present in the database.

Kaiming He, Xiangyu Zhang, and their team in paper [11] used Deep Residual Learning for the face recognition task. They have used the ResNet-152 model to recognize the face. In ILSVRC [12] competition, they have achieved 1st position by using this model.

Since deep learning algorithm gives good performance in any real-life task, Pinaki Sarkar and his team member are in their paper [13] used the deep learning methodology to implement automatic face detection. Their proposed approach is divided into two parts: 1) face detection 2) face verification. The face verification task performance is dependent on how efficiently the face verification algorithm gives the result. For the face detection phase, they have used the approach discussed in the [10] paper. For the face recognition part, they have used the transfer learning approach, first train the model on the LFW database, and then fine-tuned it on the classroom dataset. The model achieves 98.67% recognition accuracy on the LFW database while gives nearly 100% accuracy on the classroom dataset.

Angelo G. Menezesl and his co-authors in this paper [14] demonstrated the deep one-shot learning for the automatic attendance system. Their overall proposed approach is shown in figure 3. Using a single image of the class, student attendance will be recorded. Using high definition camera the class attendance will be taken and that image is passed to the face detection phase. In the face detection phase, HOG detector and pre-trained CNN



detector are used, they have implemented using dlib [15] library.

Before passing the segmented face to the facnet, an alignment operation is performed. Using the dlib library, 96x96 aligned phase is extracted. The next step is to pass the image to the FaceNet [16] architecture model for feature extraction. For face verification, a threshold-based Euclidean distance face embedding approach is used. The system will store the output present or absent in the face verification phase.

Figure 3: Proposed approach for deep one-shot learning.

For classroom attendance system, many hardware are required i.e camera, a dedicated system that contains the high-end configuration. To reduce the cost of the hardware, A.S. Hasban, N.A.Hasif and their team member in paper [17] use Raspberry Pi and Raspberry Pi night vision, which is capable of extracting a student's face from a video stream filmed by the camera. OpenCV library of image processing is installed in Raspberry pi hardware to extract essential features from images. The mission is broken down into three stages. Phase 1 is data collection, Phase 2 is recognizer training, and Phase 3 is testing. Raspberry Pi uses the Python 3 interpreter.

3. Face Recognition Framework

The researcher developed many frameworks, which provide real-time face recognition with good accuracy using a machine learning algorithm. A facial recognition (FR) system code-named DeepFace [18] is developed in
2014, which gives a nearly human-like performance in LFW [19] benchmark. Later DeepId3 [20], FaceNet [16] and DLIB [15] achieved the better performance than DeepFace [18]. Since LFW [19] dataset is built in the constrained environment, so the above framework may not give a good performance on the unconstrained images and video FR [21], [22], [23].

S. Arachchilage and E. Izquierdo, in their paper [24], developed the model which addresses the FR in the unconstrained environment. They have used the concept of the DCNN model of Inception ResNet-VI [25] trained with the softmax function.

Apart from the above model, VGGFace [26] is build using VGGNet [27], Baidu [28], SphereFace [29], CosFace [30], ArcFace [31]. In their paper, M. Wang, W. Deng [32] covered a concise survey of all the frameworks.

Summary Table of Literature

Sr No.	Author	Algorithm	Summary
1	Qingshan Liu, Rui Huang, Hanqing Lu, and Songde Ma. [4]	Kernel-based Fisher Linear discriminant analysis (FLDA) and Principal Component Analysis (PCA)	Using the kernel approach of the FLDA and PCA, they extracted features and got promising results on AT & T and YALE datasets.
2	Samuel Lukas, Aditya Mitra, Ririn Desanti, and Dion Krisnadi. [6]	Discrete Wavelet Transform(DWT) and Discrete Cosine Transform (DCT)	Using the DWT and DCT extracted the feature and pass to Radial Basis Function (Neural) Network (RBFN).
3	P.Wagh, R. Thakare, J. Chaudhari, and S. Patil. [8]	Eigen Faces and PCA Algorithm	To determine the important distinguishing feature of the face, eigen faces and PCA algorithm used
4	Peiyun Hu, Deva Ramanan. [10]	Face Detection Using Convolutional Neural Network, ResNet, HR - ResNet50, HR-ResNet101.	Using the pre-trained model, developed the solution, which detects the tiny faces from the image. The solution model can handle scale in-variance, image resolution, and contextual reasoning issues, and good performance on the well-known dataset is achieved.
5	Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun [11]	Deep Residual Learning and Transfer Learning	For face recognition, Deep Residual Learning is used, and the ResNet-152 model is used.

6	P. Sarkar, D. Mishra, and Subhramanyam [13]	CNN with a Spatial Transformer Network.	CNN is used with specific ResNet. For alignment, Spatial Transformer Network is used. The model gives nearly 100% accuracy on the student database.
7	Menezes, Jo˜ao, E. Llapa, C. EstombeloMontesco [14]	HOG with CNN and FaceNet architecture	For face-detection, CNN with HOG is used, and face recognition Face-Net architecture is used. The model gives consistent performance if we capture the image using a different camera.
8	P. Pasumarti, P. Sekhar [17]	OpenCV's Local-Binary Pattern Histograms (LBPH) Face Recognizer.	OpenCV is installed into the RaspberryPi hardware.Python3 is used as an interpreter, and MySQL database is used to store student data.

4. Recent Software

There are numerous open-source and paid software available in the market. They have used machine learning, and computer vision approaches to get good performance. The list depicts softwares which are extensively used and popular.

- Gigasource

It is a mobile and desktop app. It can work in both online and offline mode, gives 95% accuracy.

- Fareclock

It is a mobile app, which is cost-free. It is worked using cloud technology and provides API access.

- Attendlab

It is an android application that is working on the cloud by providing IP & GEO restrictions.

- Clockgogo

It is an android application that provides Real-time attendance tracking by providing GPS Work spot support.

- Jibble

It is an android and ios based application that provides Free Time
Attendance for Payroll, Billing or Productivity. It can also be used for the student attendance system.

- Railer

It is an android and ios based application, which uses a superior face detection algorithm.

5. Online v/s Offline Attendance System

Since student attendance is needed to take every day, Offline attendance could take more time if students and the number of the class are more. Maintenance of the student record is also required a lot of effort for offline medium. There could also be the chance of the proxy in offline mode. While in online mode, the attendance system could take less time even if the number of students and number of the class is more. There could be zero chance of an error in the system. Training of the model can require the high-end configuration of the computer, system setup and maintenance cost would higher in the online mode. Sometimes database management can require more effort when student record insertion and deletion activity performed.

6. Benchmark Dataset available for Face Recognition

In this paper, our prime focus is on the student attendance system. The student database will vary depending on the academic institution. But for testing the model performance to another prior model, there are numerous face recognition datasets available:

Database	# of Unique Images	Total Images	Description
LFW [19]	5,749	13,233	250x250 is Image dimension, 1,680 distinct people photos in the dataset.
AT&T [33]	40	400	Contains images like variation of time, lighting, facial expression, eyeglasses.
Yale Face Database [5]	15	165	Contains images like expressions, eyeglasses, lighting
FDDB [34]	2845	5171	Images are of varying size 363x450 and 229x410.

7. Conclusion

To maintain student attendance, the various model has been proposed by the researchers. Since Automated systems are fast, cost-effective, time-efficient compared to manual effort, these models reduce faculty effort to maintain attendance efforts and also help to reduce the cost of the stationary. The proposed system is expected to give the desired result. Some of the above-proposed algorithms have only been tested on the images collected from a single camera. There is a need to implement all the traditional face recognition method using various camera in the future. The resolution of the camera and the multiple angles of images taken play a paramount role.

This survey paper contains details about the well-known research paper's model. Also, includes the information related to different benchmark data sets and framework and different android and ios applications used in the real- life scenario.

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