ISSN : 3048-5320 (Online)

CSIBER International Journal - CIJ

Vol - 3, Issue No - 1, January 2025

MULTIDISCIPLIANRY JOURNAL

MAKE IN INDIA

Published by : CSIBER Press, Central Library Building, CSIBER Campus, University Road,Kolhapur-416004, Maharashtra, India.

Find the Journal Online at
https://www.siberindia.edu.in/journals
E-mail : cij@siberindia.edu.in

Contents

Implementation and Analysis of Attendance Management System using Facial Biometrics

Mohammed Shameer M C
Department of Computer Science, Farook College, Kozhikode, Kerala, India

Mubeena V
Assistant Professor
Department of Vocational Studies, Farook College, Kozhikode, Kerala, India

Habis Hassan
Assistant Professor
Department of Vocational Studies, Farook College, Kozhikode, Kerala, India

Abstract
Attendance tracking and management play a critical role in ensuring operational efficiency and academic performance in educational institutions. Traditional methods are often prone to errors, time-consuming, and susceptible to fraudulent activities. This study proposes an automated attendance management system leveraging facial recognition technology to address these challenges. The system employs the Haar-Cascade Classifier for face detection and the Local Binary Patterns Histogram (LBPH) algorithm for face recognition, ensuring high accuracy and reliability.
The research methodology includes three phases: database creation with pre-processed facial images, real-time face detection and recognition from live video streams, and attendance marking in CSV files. The system achieves a recognition accuracy of 98.15%, with performance varying based on camera orientation and lighting conditions. Experimental results demonstrate that optimal camera angles (20°–30°) significantly enhance recognition accuracy.
By eliminating manual attendance processes and integrating advanced facial recognition techniques, the proposed system reduces administrative workload and minimizes errors, offering a scalable, contactless, and efficient solution for attendance tracking. This study contributes to the growing field of biometric-based automation in education and highlights the importance of camera positioning in real-world applications.

Keywords Face Detection, Recognition, OpenCV, Attendance Management, Haar Cascade Classifier, LBPH.

Introduction
Attendance management is the practice of monitoring and tracking presence or absence of a particular person in the organization or events. The organization depends on manual or automated means to track the staff attendance. The process of tracking attendance is a complex and time consuming task (Karunakar et al., 2020). It involves recording, analyzing, and managing attendance data to ensure that the members are attending regularly and meeting the minimum attendance requirement set by the organization.
Attendance tracking and management in any educational institution is really important for a few reasons. Firstly, it directly correlates with academic performance as students who attend classes regularly are more likely to engage with course materials, participate actively, and perform better in assessments. Monitoring attendance aids in identifying students at risk of academic setbacks or dropout, thereby facilitating timely intervention, action and support mechanisms to ensure their retention and progression (Kamil et al., 2023). Efficient attendance management allows institutions to allocate resources effectively, optimize classroom scheduling, and deploy faculty efficiently, thereby enhancing operational efficiency. In short, attendance management is key to ensure students learn well, do well and institution runs smoothly.
In this article, we propose an attendance tracking and management system that makes use of face detection and face recognition techniques. Face detection is used to identify and locate the faces in the classroom video or image and extract sub images for each face. In face recognition, the facial images detected will be compared with images stored in the database consisting of images of the students in the class, and their attendance will be recorded accordingly.
Later sections of this research article are organized as follows. Section 2 reviews the existing techniques and available methods used for automating attendance management. Section 3 discusses the methodology used for the research. Section 4 explains the details of implementing the attendance management system using Haar classifier and local binary pattern histogram method for different projection angles. Section 5 analyses the result and section 7 concludes the research findings.

Literature review
Literature showcases many automated attendance management system based on facial detection. A method based on Radio Frequency Identification (RFID) for facial recognition is proposed in (Akbar et al., 2018). Accuracy of this method is very low and it requires direct line of sight for scanning and capturing the facial information. Similarly, brightness, capturing angle and occlusion can also affect the accuracy of such systems.

Another method for recording attendance based on iris biometrics is proposed in paper (Okokpujie et al., 2017). This method requires iris patterns to be stored in the database for recognition. This method captures the eye image for detection and recognizing the attendees. This method is very expensive and use of glasses and lenses causes hurdles in capturing iris patterns (Smitha & Afshin, 2020).

OpenCV provides several methods for facial image recognition, which can be categorized into traditional methods and deep learning-based approaches.

Eigenfaces

This approach uses dimensionality reduction and linear algebra concepts to recognize faces. This pioneering technique is easy to implement and thus used in various applications at that time such as handwritten recognition, lip-reading and medical image analysis (Khan et al., 2019).

PCA (Principal Component Analysis) is a dimensionality reduction technique that was proposed by Pearson in 1901. It uses Eigen values and Eigen Vectors to reduce dimensionality and project a training sample/data on small feature space. This approach is is very sensitive for light variations and relies on linear transformations. Since this method concentrate on global facial features, making it difficult to identify similar or identical faces (Kumar et al., 2022; Varadharajan et al., 2016).

Local Binary Patterns Histograms (LBPH)

Local Binary Patterns (LBP) are visual descriptors utilized for classification in the field of computer vision. They represent a specific case of the Texture Spectrum model (Song et al., 2013). LBP has proven to be an effective feature for texture classification, and research indicates that combining LBP with the Histogram of Oriented Gradients (HOG) descriptor significantly enhances detection performance on certain datasets. Additionally, various enhancements to the original LBP have been developed for background subtraction applications (He, Sang & Huang, 2011)

Fisherfaces

Fisherfaces is a technique used primarily in facial recognition and image analysis, built on the principles of linear discriminant analysis (LDA). The approach focuses on maximizing the ratio of between-class variance to within-class variance, which enhances the separability of different classes, such as various individuals' faces, in the feature space. This method effectively reduces dimensionality while preserving the discriminative features necessary for accurate classification (Anggo & Arapu, 2018).

Fisherfaces often outperforms other methods like PCA (Principal Component Analysis) in tasks where class differences are crucial. It can handle variations in lighting and pose better than some other techniques, making it more reliable in real-world scenarios. The calculations involved in determining the covariance matrices and optimizing class separability can be resource-intensive, particularly for large datasets. Fisherfaces may be affected by outliers in the dataset, which can skew the results and lead to misclassification. (Belhumeur, Hespanha & Kriegman, 1997; Anggo & Arapu, 2018).

Scale Invariant Feature Transform (SIFT)

The Scale-Invariant Feature Transform (SIFT) is a widely used algorithm in computer vision for detecting and describing local features in images. Its approach involves identifying key points in an image across various scales by constructing a scale-space representation, enabling the detection of features that remain consistent despite changes in scale and rotation. SIFT extracts distinctive descriptors around these key points, which are robust to transformations, allowing for effective matching across different images.

SIFT features are resilient to changes in scale, rotation, and illumination, making them highly effective for object recognition in diverse conditions. SIFT is versatile and can be applied to various tasks, including image stitching, 3D reconstruction, and tracking. It produces rich, distinctive descriptors that facilitate accurate matching between images. SIFT can be computationally intensive, particularly in generating scale-space representations and extracting descriptors, which may hinder real-time applications. In images with many repetitive textures, SIFT may struggle to distinguish between features, potentially leading to incorrect matches. (Jubair, Mahna & Wahhab, 2019; Nixon & Aguado, 2020).

Speed Up Robust Features (SURF)

Speeded Up Robust Features (SURF) is a computer vision algorithm designed for object recognition and image registration, focusing on detecting and describing local features in images. The approach utilizes a Hessian matrix-based measure to identify key points in an image, allowing for rapid computation and scale-invariance (Bay ,Tuytelaars & Van Gool, 2006). SURF features are robust to changes in scale and rotation, making them effective for matching objects across different views and lighting conditions.

SURF is optimized for performance, and it exhibits strong resilience to image transformations, including rotation, scaling, and even partial occlusion, enhancing its applicability in real-world scenarios. SURF was patented, which limits its usage in some open-source applications and can complicate integration into certain projects. SURF can be sensitive to noise and image quality, which may impact feature detection in less-than-ideal conditions. The algorithm may struggle with images that have low contrast, as the key point detection relies heavily on the presence of strong edges (Bay et al., 2008).

The literature emphasis highlights that attendance management using iris scanning and RFID has many demerits in real time facial recognition. Eigenfaces and Fisherfaces are computationally intensive and may require a large amount of data for effective training.

Principal Component Analysis (PCA) used in Eigen and Linear Discriminant Analysis (LDA) used in Fisherfaces assume linear relationships, which may not adequately capture complex variations in face images. So these methods can struggle to scale efficiently with large datasets compared to deep learning approaches. The LBPH method analyzes local patterns in the given image and is less sensitive to light changes. Hence we propose to implement LBPH method in this research.

Methodology

A video stream captured using a camera is the input given to the system. Following are the major components in this automated attendance tracking system.

Haar Cascade Classifier: Object Detection using Haar feature-based cascade classifiers is an efficient method responsible for detecting facial images from video streams. It is a machine learning based approach in which cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images. This method uses features like edges, lines and other textures to identify faces using a pre-trained cascade classifier.

Face Detection: Once the Haar Cascade Classifier identifies potential face regions in an image, the face detection module refine these detections. This module analyzes the identified areas to accurately pinpoint the exact boundaries of each face, ensuring that the detection is not only reliable but also precise. By focusing on the specific contours and features of the faces within the initial regions, this process enhances the overall accuracy of face detection, making it more effective for subsequent process. This approach ensures that the system can differentiate between multiple faces and handle variations in size, orientation, and lighting conditions.

Face Recognition: The Local Binary Patterns Histogram (LBPH) is used for face recognition - identifying the camera captured image against the image already stored in the database. The Local Binary Pattern is applied to the image and compared against the pivotal pixel of the captured image, and then the histogram value is computed for the said lbp image. LBPH is capable of analyzing the variation in pixel intensities along localized regions of the facial image to create histograms.

Implementation of LBPH (Local Binary Patterns Histograms) algorithm is carried out using face recognition module available with OpenCV. The LBPH algorithm begins with training on a dataset of pre-processed face images paired with their corresponding labels (IDs). During this training phase, the algorithm extracts key features from the images by analyzing the local binary patterns, which capture texture information essential for distinguishing between different faces.

As it processes the images, LBPH builds a robust model that learns to recognize unique facial characteristics. This model then becomes capable of accurately identifying faces in new images by comparing them to the features stored from the training set. The use of pre-processed images enhances the algorithm's performance by normalizing variations in lighting, pose, and scale, ensuring that the model is not only efficient but also resilient to common challenges in face recognition tasks.

Pre-processing: Pre-processing of the facial images are performed before training the LBPH model. This process includes translating the images to its gray-scale equivalent, resizing and adjusting the images to standard dimension to ensure consistency across the dataset. Normalizing their pixel-values is also performed to enhance the model's performance by adjusting the brightness and contrast, which helps the algorithm better identify facial features.

Attendance Management: Once the individual is identified, the attendance is recorded using CSV files. This module is responsible to marking attendance using recognized images along with date and time, storing attendance and generating reports accordingly.

Implementation

Primary Database Creation and Training

The process begins with the development of an original database containing images of students by capturing live real-time videos. These videos are then split into hundreds of frames using OpenCV. Each frame undergoes conversion to grayscale, and only the faces of the students are extracted and stored as individual images. The LBPH (Local Binary Patterns Histograms) algorithm is employed for rigorous training the system, storing respective histogram values for each student's face. During attendance marking, the stored and trained images are compared against the captured images, allowing for accurate identification and attendance recording. This method leverages OpenCV for efficient video frame splitting and integrates LBPH algorithm for facial recognition, ensuring a robust attendance tracking system without human intervention. A sample data set created is shown in Fig. 1.

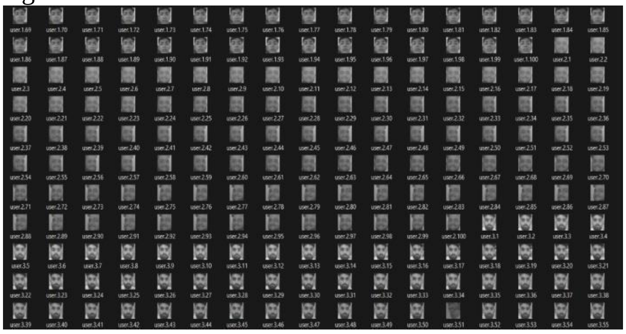

Figure 1: Data set created

System Design

The students should be registered with the system and their images should be uploaded to the database. The captured images are compared with such images to predicting the presence. In this experiment, we have loaded 20 images of each student. The complete use-case of the proposed system is as depicted in the Fig 2.

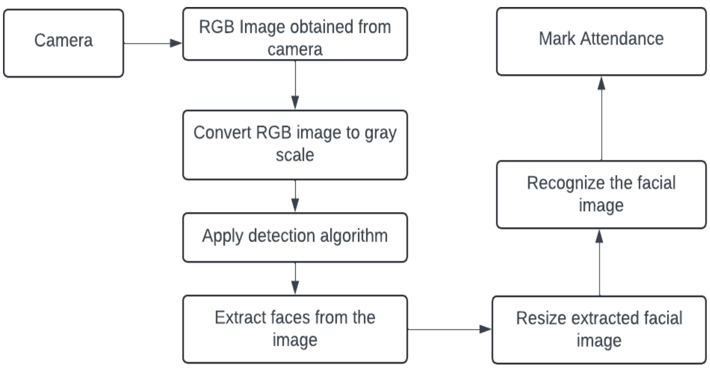

Figure 2: Image Capturing and Processing

Image Capturing

Real time videos of the class room are captured using mobile device or camera linked to laptop. In this experiment a 15 MB camera is mounted on the wall as displayed in Fig. 3.

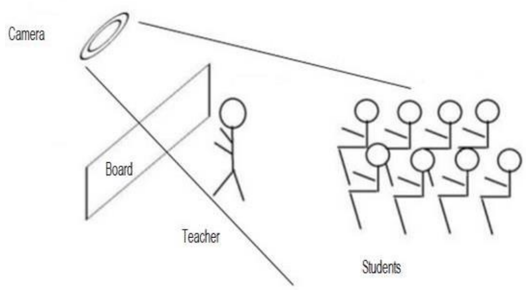

Figure 3: Capturing live videos of the classroom

Image Detection

The images extracted from the streaming videos are converted into a grey scale pattern before applying the detection algorithm. A sample generated gray-scale image is displayed in Fig 4. The Haar Cascade algorithm serves as a pivotal tool in video processing, particularly in the identification of individual faces within a frame. By leveraging Haar Cascade, the algorithm detects faces by recognizing patterns of contrast between light and dark areas. Once identified, it meticulously extracts distinct facial features of an individual such as eyes, nose, and ears, vital for accurate and precise recognition and analysis. This process of feature extraction enables the algorithm to isolate and focus solely on the regions of interest (ROIs) within the face, optimizing computational resources by disregarding extraneous information. By employing this principle, the algorithm efficiently processes only the necessary portions of the image while cropping out irrelevant regions, thereby enhancing both accuracy and performance in facial recognition tasks within the context of student monitoring or similar applications.

Figure 4: A grey scale image generated from captured image

The detectMultiScale module of OpenCV is used for detecting images. This module consider three crucial parameters: (a) scaleFactor: it is the amount of scaling applied to the image. (b) minNeighbors: indicate the number of adjacent images to be considered. Increasing the value improves the quality of capture but reduces the number of faces detected. (c) midsize: indicates the minimum size of the object. Along with these factors, the camera angle is another important parameter that should be taken in account. An appropriate angle should be set for proper image capture. In this experiment, the scale factor is set to 1.3 and minNeighbors is given as 6. The default minSize (30,30) is chosen (Becoming Human, 2018; Nirmalayakar et al., 2012).
To analyze the importance of camera angle, we tried different angles and computer the accuracy of facial recognition.

Table No. III- Accuracy For Different Projection Angles

Angle	Accuracy
0 - 20	78%
20- 30	98.15%.
30-50	97.8%
50-90	64.2%

Image Matching

Recognize a student by comparing a captured image against images stored in a database, the LBPH algorithm (Local Binary Pattern Histogram) is employed. This algorithm extracts local binary patterns from the image, creating a histogram representation of these patterns. Each image in the database has its own histogram value, which serves as a unique identifier. When the camera captures a new image, its histogram value is calculated using the LBPH algorithm. This calculated histogram is then compared against the stored histogram values of the images in the database. By cross-checking these values, the system can determine the closest match, thereby identifying the student associated with the captured image. This method of recognition is robust and efficient, making it suitable for various applications such as attendance systems, access control, and surveillance.

Attendance Marking

If the histogram values computed for the identified image matches with the any of the image stored and available in the database, then the attendance for that student is marked in a CSV file. A value of “P” is recorded in the file to indicate the students are present and a “A” value indicate the absence or the face cannot be recognized properly. A sample attendance sheet with timestamp value is shown in Fig 5.

Roll No	Name	TimeStamp	Attendance
101	Aleena	45567.42378	P
102	Arjun	45567.43316	P
103	Habis	45567.44132	P
104	Justin	45567.42072	P
105	Mubeena	45567.44528	P
106	Shameer	45567.45628	P
107	Shayan	45567.42948	P
108	Shazil	45567.43887	P
109	Shazin		A
110	Yazin	45567.45442	P

Figure 5: Sample Attendance Marking

Result andAnalysis

An automated attendance management system that make use of biometric features to recognize and identify the students in a classroom is implemented using OpenCV is demonstrated in this research paper. The model makes use of Haar Cascade classifier and Local Binary Patterns (LBP) for feature extraction. The accuracy of the automated model is computed 98.15% from the experiment. It is also established that face recognition was sensitive to face background, light, and head/camera orientations. To highlight the importance of camera projecting angle, the experiment is repeated by adjusting the camera projection angle and it is found that optimal accuracy is obtained for an orientation of 20-30 degree. Deviating from this optimal value reduces the prediction accuracy as shown the Fig 6 given below.

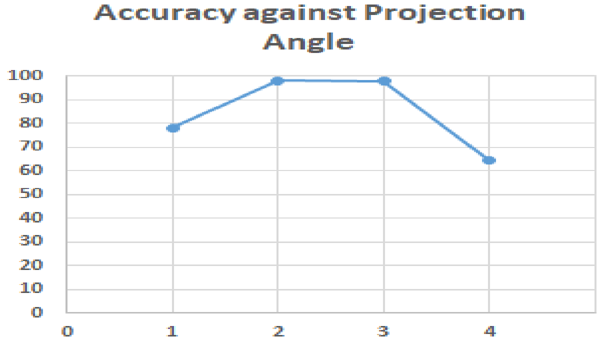

Figure 6: Facial Recognition Accuracy for different Projection Angle

Conclusion

The implementation and analysis of the attendance management system using facial biometrics records a significant technological advancement in the attendance tracking and management processes. Such a system put forth many advantages over traditional system including reduced human intervention. The system put forward a streamlined approach to identify and authorize student presence in classrooms. By utilizing facial biometrics and advanced algorithms, such as Haar Cascade and Local Binary Patterns Histograms (LBPH), the system realizes a high level of precision and accuracy and automation in attendance management.

The proposed architecture involves several key phases, including database creation and training, real-time image capturing, image detection using Haar Cascade, image matching via LBPH algorithm, and attendance marking based on image comparison. This methodology ensures efficient processing of live classroom videos, accurate identification of students, and record attendance without human intervention.

The result analysis showcases a commendable precision rate of 98.15% for the implemented model, demonstrating its effectiveness in facial image detection and recognition tasks. The performance of the proposed system is underlined by its superior precision rate over alternative methods, including LBP with PCA and SVM, LBP with KNN classification, Eigen face recognition with PCA, sensor-based methods, and CNN-based approaches.

In essence, the attendance tracking and management system using on facial biometric identification offers a robust, contactless, and convenient alternative to traditional attendance tracking methods. It not only reduces administrative workload but also minimizes the risk of errors and fraudulent activities associated with manual or card-based systems. The system's high accuracy rate and efficiency make it a valuable asset for educational institutions seeking to optimize attendance management processes and enhance operational efficiency.

References

Karunakar, M., Sai, C. A., Chandra, K., & Kumar, K. A. (2020). Smart attendance monitoring system (SAMS): A face recognition-based attendance system for classroom environment. *International Journal for Recent Developments in Science and Technology, 4*(5), 194–201.

Kamil, M. H. M., Zaini, N., Mazalan, L. L., & Ahamad, A. H. (2023). Online attendance system based on facial recognition with face mask detection. *Multimedia Tools and Applications, 82*, 34437–34457. https://doi.org/10.1007/s11042-023-14842-y

Akbar, M. S., Sarker, P., Mansoor, A. T., Al Ashray, A. M., & Uddin, J. (2018). Face recognition and RFID verified attendance system. In *2018 International Conference on Computing, Electronics & Communications Engineering (iCCECE)* (pp. 168–172). Southend, UK: IEEE. https://doi.org/10.1109/iCCECOME.2018.8658705

Okokpujie, K. O., Noma-Osaghae, E., Okesola, O. J., John, S. N., & Robert, O. (2017). Design and implementation of a student attendance system using iris biometric recognition. In *2017 International Conference on Computational Science and Computational Intelligence (CSCI)* (pp. 563–567). Las Vegas, NV: IEEE. https://doi.org/10.1109/CSCI.2017.96

Smitha, Hegde, P., & Afshin. (2020). Face recognition-based attendance management system. *International Journal of Engineering Research and Technology, 9*. https://doi.org/10.17577/IJERTV9IS050861

Khan, M., Chakraborty, S., Astya, R., & Khepra, S. (2019). Face detection and recognition using OpenCV. In *2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)* (pp. 116–119). IEEE. https://doi.org/10.1109/ICCCIS48478.2019.8974493

Kumar, A., Chaudhary, S., Sangal, S., & Dhama, R. (2022). Face detection and recognition using OpenCV. *International Journal of Computer Applications, 184*(11), 23–32. https://doi.org/10.5120/ijca2022922085

Varadharajan, E., Dharani, R., Jeevitha, S., Kavinmathi, B., & Hemalatha, S. (2016). Automatic attendance management system using face detection. In *2016 Online International Conference on Green Engineering and Technologies (IC-GET)* (pp. 1–3). IEEE. https://doi.org/10.1109/GET.2016.7916753

Song, K.-C., Yan, Y.-H., Chen, W.-H., & Zhang, X. (2013). Research and perspective on local binary pattern. *Acta Automatica Sinica, 39*, 730–744. https://doi.org/10.1016/S1874-1029(13)60051-8

He, Y., Sang, N., & Huang, R. (2011). Local binary pattern histogram-based texton learning for texture classification. In *2011 18th IEEE International Conference on Image Processing* (pp. 841–844). IEEE. https://doi.org/10.1109/ICIP.2011.6116688

Anggo, M., & Arapu, L. (2018). Face recognition using Fisherface method. *Journal of Physics: Conference Series, 1028*, 012119. https://doi.org/10.1088/1742-6596/1028/1/012119

Belhumeur, P. N., Hespanha, J. P., & Kriegman, D. J. (1997). Eigenfaces vs. Fisherfaces: Recognition using class-specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 19*(7), 711–720. https://doi.org/10.1109/34.598228

Anggo, M., & Arapu, L. (2018). Face recognition using Fisherface method. *Journal of Physics: Conference Series, 1028*, 012119. https://doi.org/10.1088/1742-6596/1028/1/012119

Jubair, A. S., Mahna, A. J., & Wahhab, H. I. (2019). Scale-invariant feature transform-based method for objects matching. In *2019 International Russian Automation Conference (RusAutoCon)* (pp. 1–5). IEEE. https://doi.org/10.1109/RUSAUTOCON.2019.8867657

Nixon, M. S., & Aguado, A. S. (2020). Low-level feature extraction (including edge detection). In *Feature Extraction and Image Processing for Computer Vision* (4th ed., pp. 141–222). Academic Press. https://doi.org/10.1016/B978-0-12-814976-8.00004-X

Bay, H., Tuytelaars, T., & Van Gool, L. (2006). SURF: Speeded up robust features. In Leonardis, A., Bischof, H., & Pinz, A. (Eds.), *Computer Vision – ECCV 2006* (Vol. 3951, pp. 404–417). Springer. https://doi.org/10.1007/11744023_32

Bay, H., Ess, A., Tuytelaars, T., & Van Gool, L. (2008). Speeded-up robust features (SURF). *Computer Vision and Image Understanding, 110*(3), 346–359. https://doi.org/10.1016/j.cviu.2007.09.014

Becoming Human. (2018). Face detection using OpenCV with Haar cascade classifiers. *Becoming Human*. Retrieved October 4, 2024, from https://becominghuman.ai/face-detection-using-opencv-with-haar-cascade-classifiers-941dbb25177

Nirmalayakar, M. K. D., Debbarma, A., Saha, A., & Pal, D. R. (2012). Study of implementing automated attendance system using face recognition technique. *International Journal of Computer and Communication Engineering, 1*(2), 134–138.

Singh, D., et al. (2014). *International Journal of Computer Science and Mobile Computing, 3*(2), 633–636.