International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I5P129
Volume 72 Issue 5, 282-289, May 2024

Original Article

Preprocessing of Dataset and Developing Smart Attendance Model Using Face Recognition

Aldinata[1*], Haryono Soeparno[1]

[1]*Department of Computer Science, BINUS Graduate Program – Master of Computer Science, Bina Nusantara University, Jakarta, Indonesia.*

[*]*Corresponding Author : aldinata@binus.ac.id*

Received: 21 November 2023 Revised: 29 March 2024 Accepted: 13 April 2024 Published: 26 May 2024

Abstract *- Attendance is one of the most widely used methods to keep track of discipline. Currently, manual attendance is in the form of RFID scans or students taking attendance from applications, with lecturers or academic persons to verify the attendance again. A smart attendance model can be used to take attendance automatically with the help of face recognition and can assist students who do not have face recognition algorithms capable able to doing such with lesser assistance. This study designs a model for smart attendance while performing the best preprocessing for both training and testing datasets to help improve the efficiency, accuracy, and effectiveness of the model. In the presented smart attendance model, training images consisting of the faces of each person will first be detected and be augmented for lighting variations before converted to face encodings and then be stored with their corresponding labels. In the testing phase, a video will be taken, in which a frame will be used as the input images to be then preprocessed to achieve the most faces possible. This is achievable by normalizing the brightness image resizing, and then face features will be extracted in the form of face encodings; before then, it will be compared to the face encodings extracted from the training phase. The results will then be divided into 3 classification tiers of accuracy, need further checking, and unrecognized face. From the experiment, the results show around 80% accurate faces, with around 20% needing further checking, and no unrecognized faces.*

Keywords *- Preprocessing, Dataset, Smart Attendance, Model, Face Recognition.*

1. Introduction

In a world marked by rapid technological advancements and innovations, simple tasks are increasingly assisted by the technologies innovated. One example is the rising use of computer vision. This enables many things to be done in a more automated way, especially attendance systems, which still use the old-fashioned way of doing it with students having to purposely do attendance in the form of an RFID scan [1], or students taking attendance from the application, with its lecturers or academic persons to verify attendance [2]. At the present times, many educational institutions have been using attendance as a measure of discipline for their students which shows how pivotal of a role attendance has in the student's learning. According to [3] indicates that attendance can gain benefits. However, a change in the way of learning, teaching, assessing, and using technology for learning is highly recommended to reverse the trend of non-attendance. The way to use technology can affect how the students would want to attend the class—especially waiting for something that they should not have. With that being said, it sparks an idea of combining both attendance with computer vision and creating a smarter way to do it where students will not need to perform something to have their attendance marked purposely, and it will be automatically done. This can be implemented by having all students' faces captured automatically inside the class before each can be recognized. The result of this research's experiments can prove the point of whether smarter, automated attendance can be performed while minimizing the student's effort to not having to do attendance marking themselves to the absolute minimum purposely.

2. Related Works

In previous research, automated attendance systems using face recognition were explored [4]. However, the researchers can only detect one face at a time, which also means that it is just at least as efficient as the old-style attendance taking, if not less. The system itself is not automated, as the user must request recognition before the camera takes a frame of the user's frontal face. Another study proposed an attendance system combining the Internet of Things with face recognition [5]. It involves retrieving data from a server, enhancing images through histogram equalization and noise filtering, and performing feature extraction. The system utilized preprocessing techniques like gray scaling, histogram normalization, median filtering, and skin classification before employing the Viola and Jones algorithm for face detection and eigenface-based recognition. The research investigated the impact of parameters on face recognition results [6] 4 parameters such as pose estimation (how a face is oriented in yaw, roll, pitch, etc.), image sharpness (how blurry an image is taken), resolution (image size), and brightness of an image were analyzed in its effects on face recognition. [7] used a high-definition camera for external access to classrooms and an internal camera for face detection and recognition to mark their attendance. They employed the Viola and Jones algorithm for face detection and Principal Component Analysis (PCA) for face recognition to speed up the whole process, achieving consistency and efficiency.

Another paper introduced the Local Binary Pattern Histogram (LBPH) algorithm for face recognition, tested using a Raspberry Pi 3 model B module, Raspberry Pi camera, servo motor, and database servers [8]. LBPH has been proven as an effective algorithm as it can overcome the drawbacks of traditional attendance systems, with face recognition having the most excellent performance among other biometric systems.

The effect of distances, angles, and amount of people for face detection has been analyzed [9]. Face detection is done using Histogram of Oriented Gradients (HOG). The result shows direct proportionality between the number of people and angles. The greater the number of people present in the picture, the less accurate the results are. This has also been proved when finding the effects of distances on the detection, with further distance being less accurate from 95% in 2 feet from the camera to around only 70% in 7 feet from the camera.

Another study compared OpenCV algorithms for face recognition (Eigenfaces, Fisherfaces, and LBPH) for attendance management [10]. LBPH exhibited the best efficiency and background noise reduction. LBPH also resulted in a higher recognition rate and threshold value compared to other algorithms, making it a superior choice for face recognition’s requirements of high accuracy. [11] aimed to optimize the LBPH algorithm by introducing a Median-based version (MLBPH) to address LBPH’s sensitivity to illumination, expression, and attitude changes. Neighborhood median sampling to replace the intermediate values is used. While recognition rates improved by around 7%, lens distortion remained an issue affecting recognition rate. An image preprocessing for illumination-invariant face recognition has been introduced, significantly enhancing standard face recognition algorithms [12]. The preprocessing works by computing the illumination field and then compensates for it which mimics the human’s visual perception. The algorithm improves the performance significantly for standard face recognition algorithms across multiple databases. An example of the algorithm’s effect is improving the performance of PCA from 17.9% to 48.6%. Also, the algorithm improved the recognition accuracy among different subsets, which proves it is a consistent algorithm.

The face recognition algorithm is enhanced for attendance management system applications by using the contrast adjustment method, bilateral filter, and histogram equalization to have better image features [13]. The system uses a Local Binary Pattern (LBP) with the aim of the improvements to improve the code of LBP. The result shows that the method is very robust and accurate for facial recognition systems in real-life environments. However, the method did not address the risk of occlusion and masked faces. Face recognition improvement with the use of image preprocessing has been done before [14]. The authors used 4 different techniques: face detection and cropping, image resizing, image normalization, and image denoising and filtering.

For face detection, the author used an image-based approach, which has a window scanning technique with fixed and dynamic mask size, and a feature-based approach, where mask size is crucial for the recognition rate. For image resizing, the nearest neighbor interpolation method is used with a specified output size. For image normalization, the histogram equalization technique is used as it can help control non-uniform contrast. Lastly, for image denoising and filtering, a pixel-based filtering technique will be used for denoising and a Low Pass Filter (LPF) for filtering. A facial recognition and attendance system using dlib and face recognition libraries has been done previously [15]. The researchers pointed out that 4 things should be done ahead of the algorithm devising an attendance system, which are finding faces, the position of faces, identifying unique facial features, and identifying the person. The research uses face alignment from the face landmarks to make a face as centered as possible.

3. Methodology

3.1. Proposed Solution

The product of this research is to have optimized preprocessing combinations for a smart attendance model. The contribution will be of a model ready to be implemented with image preprocessing. Therefore, this research will focus more on preprocessing to tackle various face recognition weaknesses. This research proposes a new combination of new preprocessing algorithms with various optimizations of the old preprocessing algorithms to make them more accurate on the given datasets.

3.1.1. Model

The general model of face recognition is shown in Fig. 1. Firstly, face detection works on making sure that the faces in the images are being detected, and then preprocessing prepares the resulting faces to be preprocessed so that they will be perfect during the face recognition phase. Next, feature extraction is done to reduce the dimensions of the image to make it easier to process. Lastly, the face recognition phase is done to check whether the resulting faces match the faces saved in the database and checks on the label of the face being successfully detected.

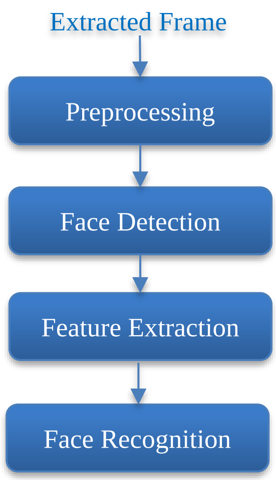

Fig. 1 Smart attendance model

3.1.2. Data Augmentation

Data Augmentation is needed to seed or enrich the input data with more variance to increase the robustness to different conditions. Sometimes, a face can appear flipped, rotated (clockwise and anti-clockwise), brighter, and even darker during the testing. With data augmentation, one single input of face can be varied to multiple images. Data augmentation also helps with overfitting as the model might "memorize" only the training data and will be compromised when there is a very different input during the testing process, such as lighting. However, the variation of images to be trained or added using data augmentation should be relevant to the scenarios that might happen in the testing phase. Irrelevance of data augmentation will make the result less accurate and require higher tolerance.

3.1.3. Preprocessing

The preprocessing part focuses on processing the image so that it will be able to show the regions of interest better for the next stages of the process to be done easily. This means that bad preprocessing can affect bad face detection (i.e., Fewer faces detected) and even face recognition (i.e., more faces recognized wrongly). There are several ways of doing preprocessing on an image, such as resizing, filtering, and normalization.

Brightness

Sometimes, classes tend to be in a position where there is insufficient lighting for the image to be considered adequate for the next step. For example, when the class curtain is closed or opened, but the lights are off, the brightness will be less and not optimal. Therefore, it is important to have some brightness normalization so that the image will be at the same level of brightness as the training dataset. Increased brightness also requires some increase in contrast, as more brightness means the image will look "whiter" than before which means more colours should be added proportionally with the amount of brightness increase.

Image Resizing

Image resizing is a way to increase the image size to help detect more faces, which also gives more features and lowers the image size to make all the images uniform in size or scale. Mostly, image resizing can help increase the number of faces detected as there will be more detailed images for face detection and feature extraction.

Image resizing involves interpolations as it is a computational technique used to estimate values between known or observed data. Common interpolation for image resizing is bicubic, bilinear, nearest-neighbour, and Lanczos interpolation, with each having its pros and cons. Lanczos interpolation puts out the highest quality result, although it is the highest in computing load. Unlike nearest neighbour, which is the fastest as it only takes the nearest neighbour as the new pixel, Lanczos interpolation involves the usage of the sinc function as the interpolation kernel.

Face Alignment

Face alignment is also needed as faces are not normally straight. It might be slanted in one direction, and it needs to be straightened. Slanted might be the only possible scenario of face alignment in 2d faces as once the face is not looking or facing the camera directly, nothing else can be done. Even warping can make one side of the face look more clear cheekbones, and the other only reaches the outer part of the cheekbone.

3.1.4. Face Detection

In the face detection phase, an estimation of which region contains the face of each chosen or randomized frame will be done. This process can be done with 2 models of either Histogram Oriented Gradients (HOG) or Convolutional Neural Network (CNN).

A Histogram of Oriented Gradients involves dividing the images into smaller cells, which later, a gradient magnitude and orientation will be calculated. The resulting gradients will be used to construct a histogram of gradient orientations for each cell before being normalized to create a feature vector. Lastly, a sliding window is used in the image to classify regions of interest using the feature vector.

Convolutional Neural Network, in contrast with HOG, involves deep learning. CNN uses convolutional layers to automatically learn features from the input image such as patterns, textures or structures that can be used for the latter. As a deep learning model, it involves training on a large dataset, but for face detection in this part, it has been pre-trained with face-specific data. Each has its advantage and disadvantages which directly correlates with each other. For instance, HOG is quicker but lacks the accuracy and detection rate of CNN. CNN is the most accurate at the expense of the high computation and memory load, unlike HOG, which is lighter than CNN.

3.1.5. Feature Extraction

Feature extraction in this part involves converting each face detected to a 128-dimensional encoding based on the features of the faces, such as eyes, nose, and mouth. This way enables the encodings to be in the form of a vector and differentiate between each face uniquely such that each faces have unique encodings to be compared with the faces previously known. Therefore, it is important to make sure that the faces are in the same alignment and size. Different sizes can put out a very slightly different encoding.

3.1.6. Face Recognition

Face recognition is a straightforward process of comparing whether the faces detected are known faces or not and who is simply in the face for each face detected based on the labels attached with the most similar face. This is made possible with the face encodings resulting in the feature extraction phase before. The results can change based on how much tolerance is allowed in the comparison, which ranges from 0 to 1.

The higher the tolerance means that the faces detected do not have to be similar to the faces known, which allows more recognition but also leaves more false recognition to be considered correct. A lower value can help mitigate false detection, but too low can leave the faces unrecognized whenever a small variation of the same person is available from the known faces and faces present during testing.

To simplify the result, a recognition tier will be used. This will make the results more classifiable. A 3-tier system will be used as follows and is summarized in Table1:

1. Tier 1: This tier will be indicated by green, and the faces classified in this tier are considered at least 95% accurate.
2. Tier 2: This tier will be indicated by blue rectangles, and the faces classified in this tier are ambiguous and need further checking if it recognizes the right faces or not.
3. Tier 3: This tier is the smallest level, where faces are detected, but it does not come close to being able to recognize within safe tolerance levels.

The point of the 3-tier system is to directly consider those in tier 1 to be present and recheck those in tier 2 as it might be wrong. This is a much better approach than the normal yes or no type of classification (similar to only having tier 1 and tier 3), where it can lead to false positive recognitions (person A recognized as person B).

3.2. Dataset

A dataset is needed for both training and testing. Training should be filled with filling in the model with recognized or known faces, including its labels. While for testing, a video of a real-life simulation is needed to be used for the testing. This is to be as similar as the real application, which is for classes. A camera placed right in the middle of the class is best for effective and accurate results as more does not yield a significantly higher recognition [16].

Table 1. 3-Tier system for classification

Tier	Description	Tolerance	Colour
Tier 1	Accurate	< 0.4	Green
Tier 2	Ambiguous	< 0.6	Blue
Tier 3	Unrecognizable	≥ 0.6	Red

3.3. Evaluation

A commonly used performance measure is accuracy. Accuracy in this research can be calculated by counting the number of faces correctly recognized by the number of faces to be recognized. High accuracy is needed to prove that the model is dependable and able to recognize the maximum number of faces without compromising accuracy. Normally, the number of faces recognized correlates to reduced accuracy; it can go higher, but it does not mean it would absolutely be accurate at the same time.

$$Accuracy = \frac{correct\ recognition}{total\ instances} \tag{1}$$

As it has been stated before, this research outputs 3 tier classifications. Therefore, correct recognition represents both tier 1 and 2 classifications that are correct, as it may still be wrong (especially tier 2). Another used performance measure is time. Time is measured for each of the testing processes, starting from preprocessing up to face recognition, face encoding conversion, and face recognition.

4. Results and Discussion

4.1. Training

In this study, the smart attendance model is intensively studied on the personally collected dataset of one class consisting of 12 persons. The dataset holds 50 picture samples with 2 different quality classes of low and high. The quality of the images is good, with only 10 classified below 500x500px, as portrayed in Table 2 and Fig. 2.To continue the face recognition, a model is trained from the input images mentioned above. A face must be detected from the input images before it can be preprocessed with face alignment. Face alignment itself makes use of the face landmarks present in the face, such as the original position of the left and right eye, to make an angle relative to normal. Then, after a rotation is Figured out, it will be aligned, as shown in Fig. 3. Then, with the faces detected and the image aligned, it is cropped only to take a single face, which is resized to a uniform size of 250x250px using Lanczos interpolation, as shown in Fig. 4.

Right after that, each face image is augmented by adding a variation of it being darker and brighter by 25% and with less and more contrast by 5 units, respectively. It is done to make the resulting face more robust to lighting differences in the testing phase; examples of this are shown in Fig. 5. Lastly, each of the augmented images will be feature extracted to 128d encodings and is labelled based on the person it is for later use in recognition of the testing phase.

Table 2. Image quality distribution

Image Quality	No. of images
<= 500x500 (Low)	10
> 500x500 (High)	40
Total Images	50

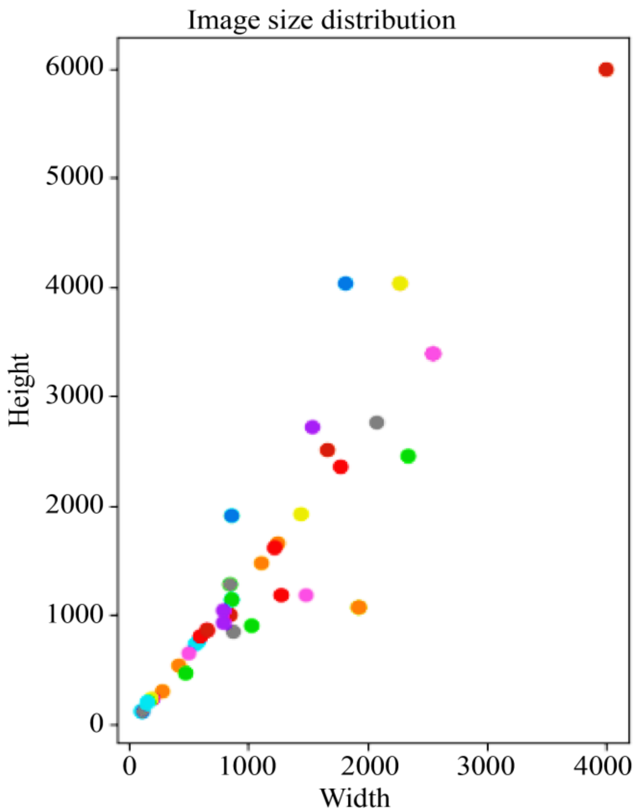

Fig. 2 Image dataset size distribution

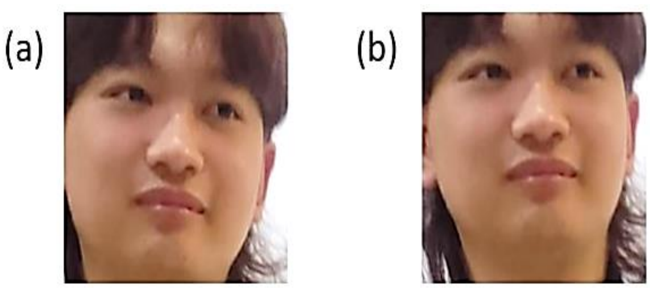

Fig. 3 Results of face alignments: (a) original face, (b) aligned face

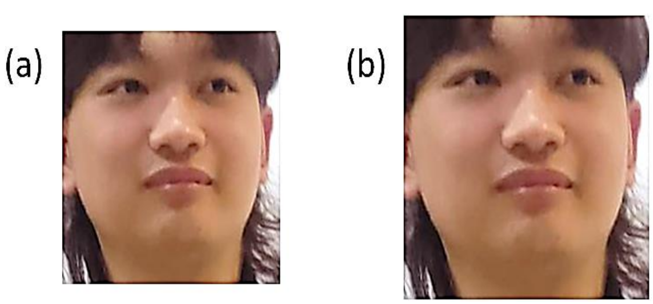

Fig. 4 Results of image resizing: (a) aligned face, (b) resized face

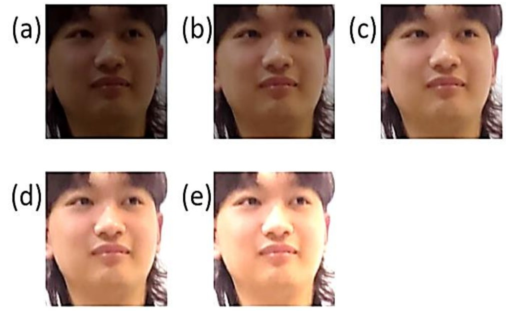

Fig. 5 Examples of augmented data: (a) 50% less contrast and 20 units darker, (b) 25% less contrast and 10 units darker, (c) original image, (d) 25% more contrast and 10 units brighter, and (e) 50% more contrast and 20 units brighter

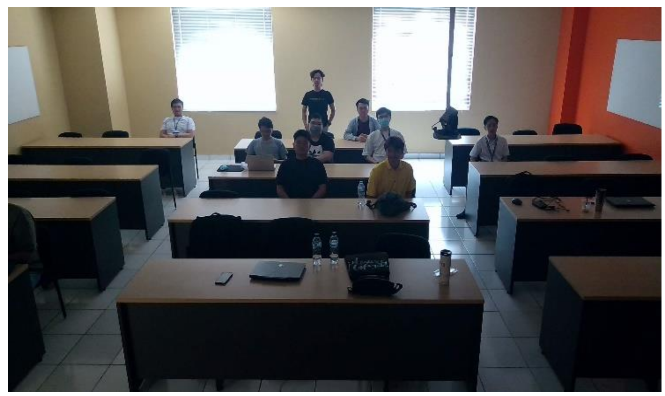

Fig. 6 Example of low-light image

Fig. 7 Brightened image

Fig. 8 Face detection results

4.2. Testing

In the testing phase, the video of a class in action is used and a random frame is extracted from the video to do a recognition. The chosen frame for testing is frame 5610 of 7354 frames. Before doing other preprocessing, the image will be checked on its brightness. The chosen frame has around 93.26 brightness, which lacks around 7 brightness to reach the target of 100.

Therefore, it will be brightened by a factor of 1.07. However, an example of a scenario of low light is shown in Fig. 6, where it has only 80 brightness, which means it will be brightened by around 20 points to achieve the optimal 100 mark, as shown in Fig. 7. Then, after brightness normalization is done, it proceeds to image resizing to enlarge it to twice its size to enhance face detectability using Lanczos interpolation. Then, faces are detected and resulted as shown in Fig. 8.

The next step is feature extraction, which converts all the detected faces to the form of vectors to be compared with the known faces resulting from the training data. A tolerance of 0.25 is set as the default value for the classification.

Unless the faces are not recognized, the tolerance will be loosened by 0.01 until it either finds a match or hits the maximum possible tolerance of 0.6. It will be deemed as unrecognized faces (tier 3 classification). During the process, when a face is finally recognized, the amount of tolerance a face is recognized is used to determine whether it is a tier 1 or tier 2 classification. The results of the face recognition are shown in Table 3 and Figure 9.

Table 3. Classification tier results

Tier	Number of faces	False Recognition
Tier 1	8	0
Tier 2	2	0
Tier 3	-	0
Total	10	0

Table 4. Comparison of face detection algorithms

Algorithm	Faces Detected	Detection Rate	Time Needed
Viola & Jones	10	100%	9.28s
HOG	10	100%	4.92s
CNN	10	100%	43.76s

Fig. 9 Face recognition result

4.3. Discussion

The result recognizes 8 persons: Bagas, Owen, Jason, Juanrico, Franky, Hansen, Hendri, and Vito to be tier 1 classification which is the true positive (correct recognition). However, only 2 of the classifications fall to tier 2, which are Aldinata and Faiz. Although it falls to tier 2, it is still a true positive meaning it is a correct recognition. This might be affected by either the lack of video quality 3840x2160 pixels being used to identify a face around 7 to 10 meters from the camera, an exceptionally low tolerance of 0.40, or an inadequate dataset for the persons recognized in tier 2 classification used for this case.

However, none of the faces falls into the tier 3 classification, which means it can recognize people with high confidence and accuracy. This paper proposes the use of HOG for face detection, as faces should be detected as much as possible while still maintaining time complexity to the minimum. A comparison of algorithms can be seen in Table 4. HOG turns out to be the superior algorithm as it can detect all the faces present inside the extracted frame fastest while having the same result as the other algorithm (Viola & Jones and CNN). This also proves that the use of HOG is best as it only requires 4.92 seconds to detect all persons inside the image, which averages at around 0.4 seconds per person.

The use of multiple tiers for the recognition of faces can be considered a success. This is proven by only 2 persons requiring verification, which is classified as tier 2 recognition. If multiple tiers are not used, then the so-called “grey area” in tier 2 will either be considered as tier 3 or unrecognized, which requires verification to find the students associated, or tier 2 will be considered as tier 1, meaning a looser and more tolerate classification is performed, which might lead to more false positive recognitions.

5. Conclusion

To conclude this research, the preprocessing methods presented have shown a high accuracy and require less tolerance, which allows the model to be more precise. No false positives are present in the results, even if it is not tier 1 classification as tier 2 classifications recognize the right faces without mistake but only that it is prone to being not precise in certain occasions, especially for tier 2 classifications as it is considered as the middle between correct and wrong (or unrecognized) classification.

Overall, the system is able to guarantee around 80% accurate faces recognized, 20% of faces unguaranteed to be recognized accurately, and no faces unrecognized with no 0 but undetected faces. This gives a huge confidence that using face recognition for a smart attendance model is optimal and can be used in real-life scenarios to help with doing automated and smarter attendance, which is used as disciplinary measures with very little to no human assistance or operating the system apart from verifying the recognition results.

References

[1] S. Kurniali, and Mayliana, "The Development of a Web-Based Attendance System with RFID for Higher Education Institution in Binus University," *EPJ Web of Conferences*, vol. 68, no. 38, pp. 1-5, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[2] Alif Fatihi Abdul Fatah et al., "Student Attendance System Using an Android Based Mobile Application," *11th IEEE Symposium on Computer Applications & Industrial Electronics*, Penang, Malaysia, pp. 224-227, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] P. Massingham, and T. Herrington, "Does Attendance Matter? An Examination of Student Attitudes, Participation, Performance and Attendance," *Journal of University Teaching and Learning Practice*, vol. 3, no. 2, pp. 20-42, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[4] Nirmalya Kar et al., "Study of Implementing Automated Attendance System Using Face Recognition Technique," *International Journal of Computer and Communication Engineering*, vol. 1, no. 2, pp. 100-103, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[5] Priyanka Wagh et al., "Attendance System Based on Face Recognition Using Eigen Face and PCA Algorithms," *International Conference on Green Computing and Internet of Things*, Greater Noida, India, pp. 303-308, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] Shubhobrata Bhattacharya et al., "Smart Attendance Monitoring System (SAMS): A Face Recognition Based Attendance System for Classroom Environment," *IEEE 18th International Conference on Advanced Learning Technologies*, Mumbai, India, pp. 358-360, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Shreyak Sawhney et al., "Real-Time Smart Attendance System Using Face Recognition Techniques," *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, pp. 522-525, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] A. Arjun Raj et al., "Face Recognition Based Smart Attendance System," *2020 International Conference on Intelligent Engineering and Management (ICIEM)*, London, UK, pp. 354-357, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Kaneez Laila Bhatti et al., "Smart Attendance Management System Using Face Recognition," *EAI Endorsed Transactions on Creative Technologies*, vol. 5, no. 17, pp. 1-5, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] Sudhir Bussa et al., "Smart Attendance System Using Opencv Based on Facial Recognition," *International Journal of Engineering Research & Technology*, vol. 9, no. 3, pp. 54-59, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Xue Mei Zhao, and Cheng Bing Wei, "A Real-Time Face Recognition System Based on the Improved LBPH Algorithm," *IEEE 2nd International Conference on Signal and Image Processing (ICSIP)*, Singapore, pp. 72-76, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ralph Gross, and Vladimir Brajovic, "An Image Preprocessing Algorithm for Illumination Invariant Face Recognition," *4th International Conference on Audio-and Video-Based Biometric Person Authentication*, Guildford, UK, pp. 10-18, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[13] Serign Modou Bah, and Fang Ming, "An Improved Face Recognition Algorithm and its Application in Attendance Management System," *Array*, vol. 5, pp. 1-7, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Krishna Dharavath, Fazal Ahmed Talukdar, and Rabul Hussain Laskar, "Improving Face Recognition Rate with Image Preprocessing," *Indian Journal of Science and Technology*, vol. 7, no. 8, pp. 1170-1175, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[15] Shashank Reddy Boyapally, and K.P. Supreethi, "Facial Recognition and Attendance System Using Dlib and Face Recognition Libraries," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 3, no. 1, pp. 409-417, 2021. [Google Scholar] [Publisher Link]

[16] Louis Mothwa, Jules-Raymond Tapamo, and Temitope Mapati, "Conceptual Model of the Smart Attendance Monitoring System Using Computer Vision," *2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, Las Palmas de Gran Canaria, Spain, pp. 229-234, 2018. [CrossRef] [Google Scholar] [Publisher Link]