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Development of Automated Attendance System Using Pretrained Deep Learning Models

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***Abstract* - Smart classroom enables better learning experience to the students and aid towards efficient campus' management. Many studies have shown positive correlation between attendance and student's performance, where the higher the attendance, the better the student's performance. Therefore, many higher learning institutions make class attendance compulsory and students' attendances are recorded. Technological solutions for an advanced attendance system such as face recognition are highly desirable. Face recognition offers an automated, smart, and authentic solution in recording student attendance. In this work, an artificial intelligence-based face recognition system is used for attendance recording system. The recognized face is used to confirm the presence of a student to the class. Six pretrained face recognition models are evaluated for the adoption in the system developed. FaceNet is adopted in this work with accuracy of more than 95%. The automation system is supported by IoT.**

Keywords—Attendance System, Face Recognition, FaceNet

I. Introduction

Smart classroom incorporates technology in a classroom setting giving better learning experience to the students and aid in campus management for teachers and the administrative personnel [1],[2]. Studies show positive relation between attendance and student's performance [3]. Based on the studies, students with higher classroom attendance are reported to have better performance. Therefore, class attendance is usually made compulsory, and the students' attendances are recorded.

The conventional attendance system includes a lecturer calling out student names one by one. Other methods are circulating attendance lists for students' signatures and displaying QR codes during class. These methods are insecure as signatures can be forged and QR codes can be shared. Biometric solutions ensure the authenticity of students' attendance by examining a student's unique physical attributes. It is better compared to RFID access card as it cannot be stolen and is hard to replicate. An example of biometric solution is using thumbprint. The thumbprint is unique. However, an important lesson learnt from Covid-19 is that it is advisable to avoid physical contact via shared surfaces. Biometric solution like thumbprint requires users to scan their thumbprint on the same surface.

Face recognition is another biometric identification method. It analyses a person's facial attributes and can be used to authenticate a student's attendance and presence in a classroom. It can be paired with proximity sensor to ensure no physical contact is required.

This work proposed a solution where the classroom is installed with an advanced face recognition system for

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recording attendance. A standard face recognition system has two primary stages: face detection process before face recognition. Two types of algorithms that are used for face recognition systems are machine learning and deep learning. Pretrained deep learning algorithm is employed in this study. In the context of robustness and uncertainty challenges, it has been observed that pre-trained models often outperform the models that are trained from scratch. It has been observed that utilizing pre-trained models lead to notable enhancements in the accuracy of predicted uncertainty estimations [4]. Six pretrained face recognition models are evaluated; FaceNet, OpenFace, DeepFace, DeepID, ArcFace and VGGFace. Based on the accuracy and the FaceNet is adopted for the proposed solution.

This work is divided into five sections. Related works are reviewed in section 2. The six evaluated pretrained face recognition models are presented in the next section followed by the discussion of the results obtained in section 4. Lastly, the work is concluded in section 5.

II. RELATED WORKS

Face recognition systems are mainly used to verify a person's face and are often used for security purposes. There are two main parts of the system which are face detection and face recognition. Face detection is a process of detecting available faces in an image or video frame and cropping the faces and applying corrections to the cropped faces. Face recognition encodes the cropped faces and produces vectors containing the faces information. Lastly, a distance classifier is used to measure the similarity between two sets of vector representation of faces. Two main types of algorithms used in face recognition system are Machine Learning (ML) and Deep Learning (DL). These are two main categories of Artificial Intelligence (AI) algorithms.

Siamese convolutional neural network (SCNN) has been used for the purpose of registering attendance [5]. SCNN compares the similarity of two input images. SCNN utilises two parallel CNN in which each input image is fed to one of the two parallel CNN. The parallel CNN used in SCNN is of the same algorithm. The encoded images from the parallel CNN are compared with each other by using a distance classifier. If the distance is below a certain threshold, the image pair are considered by the program to be of the same person. The network used is FaceNet, a pre-trained DL network. The proposed system saves 50 images of each student in their database. The advantage of SCNN is the training time is short and requires a small amount of data for verification. If a face captured is recognized by the system, an attendance is added in MySQL database. The database is accessible through APACHE interface which is a web-server.

In [6], a face recognition system is deployed to verify university students' attendance. ML algorithms are used in the developed system instead of DL algorithms. Viola-Jones algorithm is used for face detection process. Logistic regression (LR), linear discriminant analysis (LDA), and k-nearest neighbour are used for face recognition process. Machine learning algorithms were chosen because of lower computational cost. DL algorithms are more computationally expensive to run. The algorithms tested were able to achieve maximum accuracy of 97.48% by using LR.

Face detection attendance compared in [7] are Multi-task Cascaded Convolutional Neural Network (MTCNN) and Haar Cascade. Haar Cascade is a ML algorithm while MTCNN is a DL algorithm. MTCNN can get a precision of 98.02% compared to 95.24% by using Haar Cascade. Although MTCNN can achieve higher accuracy, it is much more computationally expensive. The system is based on a low power board which is Raspberry Pi, so it is necessary to choose a more computationally efficient algorithm. Therefore, Haar Cascade was chosen as the face detection algorithm. The algorithm is paired with FaceNet for face recognition process. After a student has been recognized by the system, a record of the student is saved to a CSV file as attendance.

In [8] face recognition method is used for filling exam form. OpenCV is used for image processing. Liveness detection in OpenCV can detect fake faces such as images and videos on screen. The system uses webcams to take images of students. After that, the image goes through an image enhancement process. For the face detection process, Histogram of Oriented Gradient (HOG) was used. The cropped image is fed to FaceNet to perform face recognition. The encoded data by FaceNet is then compared to data in database by using SVM classifier. The closest match is then stored as attendance. After that, the system automatically searches for the data of the recognized person in the university database and fills in the exam form of the student.

Image quality of input images and training images are important factors. Therefore, Local Binary Pattern (LBP) algorithm and image processing is proposed in [9]. The images are processed to improve the quality. First, contrast adjustment method is applied on input face images. Then, the image is filtered using bilateral filter. Lastly, the image is equalized using image histogram equalization. By using this method, the accuracy is improved from 91% to 95%. The dataset is then improved further by applying linear blending of 0.5 alpha. By improving the dataset, face recognition accuracy is improved to 99%. The attendance system introduced can track more than one face and save attendance information such as enter and exit times.

In face-recognition based attendance system in [10], Haar Cascade is used for face detection while AdaBoost classifier is used for face recognition. Before the face detection and face recognition process, the students need to input their face images and their information in a Graphical User Interface (GUI) and the information is then saved to the database. The developed system was able to recognize multiple images at a time. After a face has been recognized, a record of the student is added to an attendance sheet. The main advantage of this algorithm is fast training and low computational cost.

YOLO is an object detection algorithm and was implemented in [11] using transfer learning for face recognition application in library attendance system. The YOLO version chosen is YOLOv5. To train the YOLOv5, 1420 images are used. The training process is completed in 3 hours and 44 minutes with 1000 epochs. The trained model can reach a precision of 0.9884. The library attendance system not only can detect and recognize faces but also recognize objects such as facemasks. The attendance system utilizes a real-time video to record attendance of visitors. The recorded attendance is uploaded to the university database.

From the existing works, various ML and DL algorithms for face detection and recognition have been adopted by researchers and incorporated into automated attendance systems. Pretrained models such as FaceNet are popularly adopted. Additionally, the researchers noted that image quality plays an important role in the accuracy of a face recognition system.

III. PROPOSED FACE RECOGNITION ATTENDANCE SYSTEM

The proposed system needs to take the student's attendance automatically. The location of the camera is important in ensuring the performance of the system. Putting the camera in front of the classroom door has a high possibility of the face is obstructed by object or other students. For example, when a group of students rushes in the class at the same time, some faces can be blocked by other students and students that wear masks are not detected by the face recognition system. This will lower accuracy and cause inconsistent performance. To solve this problem, the camera is placed in a designated area within the classroom with good lighting, the students are required to stand directly in front of the camera to record the attendance. A camera light is used to illuminate the student and provide sufficient illumination for image taking. According to [12], face recognition system has lower accuracy if the image taken in bad lighting. An important aspect to consider is bottleneck avoidance at the attendance taking station.

The attendance system design is developed using combination of hardware and software solutions. Raspberry Pi Zero 2 W (RPZ2W) is placed inside the classroom together with the NodeMCU ESP8266, a small display, a camera light, the camera, and proximity sensors. The ESP8266 NodeMCU is used to control the camera light and the small display. NodeMCU ESP8266 is also used to collect sensor data from ultrasonic sensor (proximity sensor). The NodeMCU ESP8266 is connected to the WLAN and transmit the sensors data to the Blynk IoT server and RPZ2W. A camera is used to take the pictures of students. It is connected to RPZ2W. where the RPZ2W provides command according to the output of the proximity sensor. If the proximity sensor detects a nearby object or person, it turns on the camera light and alerts RPZ2W to on the camera to take a picture. The picture is sent to a computer server. Result of the face recognition process is sent to a small display. The proposed system is shown in the block diagram in Figure 1.

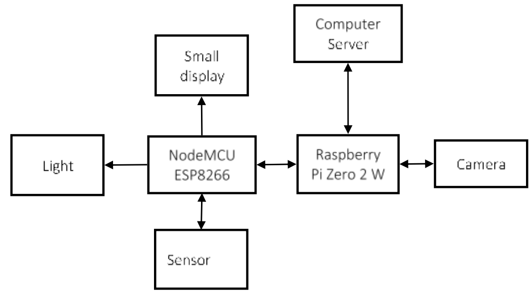


FIGURE 1. Proposed system.

Face Recognition algorithms used in this project is based on deep learning. Single Shot Detector (SSD) face detection algorithm used here. Meanwhile, six pretrained face recognition algorithms; FaceNet, OpenFace, DeepFace, DeepID, ArcFace and VGG-Face are evaluated.

A. FaceNet

FaceNet was introduced by researchers at Google in 2015 [13]. FaceNet uses a deep convolutional network. FaceNet is using triplet loss function to train its output as 128-D embeddings. The CNN was trained using Stochastic Gradient Descent (SGD) with standard backpropagation and AdaGrad. FaceNet was trained using 100M to 200M images consisting face thumbnails of 8M different person. The algorithms performed quite well and can achieve an accuracy of 99.63% in the LFW dataset. In YouTube Faces (YTF) database, the algorithm achieved an accuracy of 95.12%.

B. OpenFace

OpenFace is considered as a simple model for face recognition [14]. OpenFace used techniques implemented in DeepFace and FaceNet for face recognition with neural networks. FaceNet's triplet loss is used in OpenFace. The original OpenFace algorithm is a set of tools that can be used for detecting face landmark, face recognition, eye-gaze estimation, and head-pose approximation. As this project is only for face recognition, the only focus is on the usage of OpenFace's face recognition ability. The output from OpenFace neural networks is a representation consist of 128-d vectors.

C. DeepFace

DeepFace was developed by researchers at Facebook (FB) [15]. The algorithm was used to detect faces in images posted on FB and tag the person's Facebook account to the posted image. An additional step is introduced into the normal face recognition pipeline by adding a step to employ 3D face modelling to apply piecewise affine transformation to generate a face attribute representation. DeepFace was tested on both LFW and YTF dataset. Accuracy achieved for YTF dataset is 92.5%. For LFW dataset, the algorithm achieves an accuracy of 97.5%.

D. DeepID

Deep hidden Identity features (DeepID) is used for face verification [16]. Facial landmarks perceived by DeepID are two eye centers, nose, and two corners of mouth. The algorithm is trained using CelebFaces that has a total image of 87,628 images of 5436 celebrities available on the internet. Besides, to increase the performance of the system, a larger dataset is used which is CelebFaces+. The data contains 202,599 images containing face of celebrities. The algorithm's performance is tested by using LFW dataset. DeepID achieves 97.45% accuracy on LFW.

E. ArcFace

ArcFace was introduced in 2015 by researchers at Imperial College of London [17]. ArcFace uses Additive Angular Margin Loss, which is a loss function that is utilized in face recognition process. Other loss functions that are commonly used are triplet loss and softmax. ArcFace achieves high accuracy in LFW dataset which is 99.83%. By default, the similarity distance between faces used in ArcFace is cosine distance.

F. VGGFace

Visual Geometry Group (VGG) of University of Oxford introduced VGG Face back in 2015. VGG Face was designed for face recognition. Triplet loss is used to improve the performance of VGG during identify verification process. LFW and YTF is used to evaluate the performance VGG Face. VGG Face can reach an accuracy of 98.95% on the LFW dataset. For YTF dataset, the algorithm achieves an accuracy of 97.3%.

IV. RESULTS & DISCUSSION

The first experiment conducted is to evaluate the performance of the six pretrained face recognition models identified. The objective of the experiment is to identify the best face recognition algorithm for the deployment of the attendance system. The second experiment is conducted using the selected face recognition algorithm with an aim to study the factors to ensure successful deployment of the attendance system. The attendance is recorded based on face detection.

A. Evaluation of Face Recognition Pretrained Models

The Sefik Serengil Deepface test dataset [18] is used to compute the accuracy of the tested algorithms. The dataset consists of 61 images. Additional images of 16 individuals are added to the dataset, which sums the total images to 78 images. The images are labelled with the name of individuals and paired with each other with a total of 1596 pairs, of which 1490 image pairs are of different person and 106 pairs are of the same person.

The faces are detected using SSD before face recognition by the pretrained models. The images are fed into the respective face recognition algorithms. The performance of the algorithms in terms of accuracy and encoding time are recorded and tabulated in Table 1.

TABLE 1. Performance of pretrained models.

No.	Algorithms	Accuracy	Average encoding time (ms)
1	FaceNet	95.30%	54.9
2	OpenFace	93.36%	28.4
3	DeepFace	93.42%	66.0
4	DeepID	93.42%	22.5
5	ArcFace	94.05%	98.9
6	VGG-Face	94.11%	229.6

FaceNet can reach the highest accuracy compared to the algorithms tested at 95.30%. Second place for accuracy is VGG-Face with an accuracy of 94.11%. However, VGG-Face is much slower compared to FaceNet. VGG-Face takes 229.6ms to process a pair of images while FaceNet is four times faster than VGG-Face, where it can take only 54.9ms.

In terms of speed, DeepID is the fastest which takes only 22.5ms to process an image pair. However, the accuracy of the DeepID algorithm is 93.42% which is lower than FaceNet.

FaceNet has the best balance between speed and accuracy. It can score good accuracy results and can quickly encode the images. Hence, FaceNet is adopted for the attendance system proposed in this work. The output of the face recognition is shown in Figure 2. The algorithm did not check for live images as can be seen with the recognition of still images of Johnny Depp, Rowan Atkinson, and Angeline Jolie.

FIGURE 2. Face recogntion output.

B. Deployment of the Proposed System

In this experiment the camera is placed in front of the students and students need to queue in front of the camera. An ultrasonic sensor, HC-SR04 is used as the proximity sensor. A student needs to put their hand in front of the sensor for the system to automatically take a picture of the student. When a picture is taken, the screen displays the result of the face recognition process. If the face recognition is successful, the display shows the text "verified!" on the screen. On the other hand, if face recognition is not successful due to error and no similar faces, the screen displays the text "Try again". A camera light is used to increase the image quality and ensure consistent lighting.

For the student's image to be recognized by the algorithm, the system needs to have a database that consists of all the students' face images. The database consisting of 13 students is used in this experiment. Before the experiment, all the students' images are included in the database and are trained using the FaceNet algorithm.

1) Light

An attendance system that takes images with lower quality due to bad lighting has a higher chance of failing to correctly identify the student's identity. Therefore, the placement of the camera plays an important factor. A test is conducted where the photo taking station is placed outside of the classroom where the lighting is poor. The environment of the testing can be viewed in figure 3.

FIGURE 3. Photo station in poor lighting.

The resulting image from this automatic attendance process is shown in Figure 4. The resulting image is very low quality due to the poor lighting. The participants require a few tries to make sure their face is recognized by the face recognition system. However, most of the time, the algorithm failed to recognize the person in the picture. However, if the image quality is acceptable and the algorithm can recognize the person in the image the participant's attendance is recorded. The recorded participant attendance list is shown in Figure 5 where the system recorded the name and time the attendance is taken.

From this experiment observation, the algorithm needs to have decent lighting to be able to correctly detect and recognize a student's face. This can be achieved by installing camera light and by choosing a more suitable place, such as indoors with better lighting.

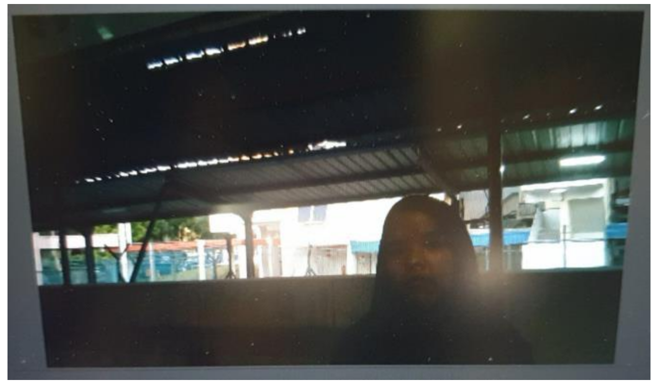
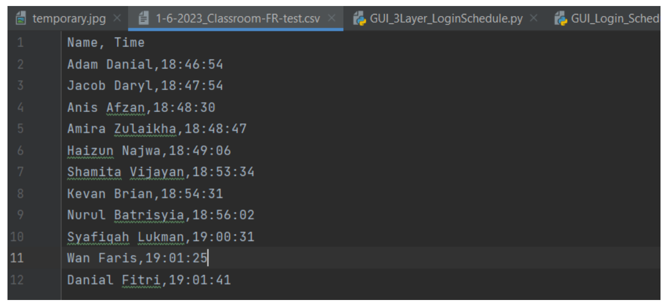


FIGURE 4. Poor image quality.




```
Name, Time
Adam Danial,18:46:54
Jacob Daryl,18:47:54
Anis Afzan,18:48:30
Amira Zulaikha,18:48:47
Haizun Najwa,18:49:06
Shamita Vijayan,18:53:34
Kevan Brian,18:54:31
Nurul Batrisyia,18:56:02
Syafiqah Lukman,19:00:31
Wan Faris,19:01:25
Danial Fitri,19:01:41
```

FIGURE 5. Recorded participant list.

2) Camera distance & angle

Camera angle and distance affect the accuracy of the system. This is observed in an indoor experiment where the lighting is good. The experiment environment is shown in Figure 5.

FIGURE 6. Camera distance & angle experiment.

The field of view of the camera used is not big and when the camera is placed too close to a participant, some part of the face may be cropped. This reduces the chance for the algorithm to correctly recognize the face.

Since the selected face recognition model, FaceNet, processes image data by extracting the whole facial features into face embeddings, if the image is compromised by distance and angle of the camera, the algorithm is not able to be recognised the face correctly. Thus, multiple tries need to be done by the participants to be recognised by the system. One of the participants (participant 3) is not able to be recognised at all. The results from the experiment are presented in Table 2.

TABLE 2. Results from poor camera distance & angle.

Participant Name	Time Taken (s)	Number of Try	Remarks
Participant 0	5	1	-
Participant 1	4	1	-
Participant 2	29	3	Participant didn't look directly into the camera, reducing the accuracy of face recognition.
Participant 3	-	-	Camera Angle issue. Only half of participant's face was captured due to her height. The algorithm cannot correctly identify the person. Can be improved by changing the distance to camera and camera angle.
Participant 3	15	2	This result is after changing the angle of camera.
Participant 4	3	1	-
Participant 5	27	3	Camera angle problem.
Participant 6	4	1	-
Participant 7	6	1	-
Participant 8	14	2	-

After adjusting the camera distance further from the participant to allow wider angles and changing the camera angle, the accuracy increased drastically, and the time taken to recognize a participant decreased. The accuracy after the adjustment is 100% and the average time taken to recognize a participant is 4.75 seconds. As tabulated in Table 3, all participant needed only 1 attempt to be recognized by the system, including participant 3.

TABLE 3. Results from good camera distance, angle & good lighting.

Participant Name	Time Taken (s)	Number of Tries	Remarks
Participant 1	6	1	-
Participant 2	4	1	-
Participant 3	4	1	-
Participant 4	5	1	-
Participant 5	5	1	Issue with proximity sensor detecting the hand distance. The reason could be that the hand is not placed directly in front of the sensor.
Participant 6	5	1	-
Participant 7	5	1	-
Participant 9	4	1	-

From the experiments conducted, it is found that in addition to lighting, the setting of the camera station influences the performance of the system. Therefore, for successful deployment of the system these aspects need to be taken into consideration.

V. CONCLUSION

The objective of this project is to develop an automatic attendance system that utilizes DL based pretrained face recognition. To find the best algorithm for the face recognition, six algorithms are tested, and their performance are evaluated. The algorithm that has been identified and chosen is FaceNet. It can achieve an accuracy of more than 95%. In the real-world usage, the setup of the system plays a big part in ensuring the accuracy of the system is preserved. It is observed that the algorithm's accuracy is heavily impacted by the image quality. If the image is too dark or there is blurring in the image, the accuracy of the of the algorithm is significantly dropped. In future, the proposed system can be merged with the classroom appliances control. By utilizing the class information and the attendance, the appliances can be turned on and off according to the class availability. Additionally, in the future work live detection should be considered to avoid attendance forging using still images. Moreover, other applications of face recognition like recognition of driver who is driving under alcohol influence [19] or as assistive technology for visually impaired individuals [20] are to be explored.

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AUTHOR CONTRIBUTIONS

Muhammad Shahrul Zaim Ahmad: Writing – Original Draft Preparation;

Nor Azlina Binti Ab Aziz: Writing – Review & Editing;

Anith Khairunnisa Ghazali: Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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